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**Disentangling Bottom-Up and Top-Down Mechanisms Associated with Social
Information Processing in Loneliness Across Behavioral and Neural Levels of
Analysis**

[Wyodrębnianie mechanizmów oddolnych i odgórnych związanych z przetwarzania informacji
społecznych w samotności na poziomie behawioralnym i neurofizjologicznym]

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Abstract

Loneliness—defined as a subjective sense of insufficient social connection—is associated with substantial risks for physical and mental health problems, as well as premature mortality. Cognitive models propose that loneliness heightens bottom-up vigilance to social cues, functioning as an adaptive mechanism promoting social reconnection. However, this vigilance may lead to hypervigilance to social threats, fostering negative affect and biased interpretations of social environments. These reactions, in turn, exhaust top-down regulatory resources, potentially reinforcing negative social appraisals. Despite strong theoretical underpinnings, empirical support has largely been limited to self-report, with insufficient evidence regarding real-time social stimulus processing.

To address this gap, in this thesis I examine the following hypotheses: (1) whether loneliness is characterized by heightened bottom-up responses to social threats—manifested as increased automatic attentional orienting and heightened physiological affective reactions; and (2) diminished top-down regulatory control during social threat processing—reflected in reduced ability to maintain goal-directed behavior, inhibit prepotent responses, and effectively regulate emotional reactions to socially threatening stimuli. To investigate these cognitive mechanisms, this thesis integrates behavioral and self-report methods with approaches that offer deeper insights into underlying cognitive processes, namely electrophysiological (EEG/ERP) and computational modeling, across three studies. Electrophysiological measures (EEG/ERP) enable tracking neural activity in real time, providing precise temporal insights into separate stages of social stimulus processing. Computational modeling, specifically the Drift Diffusion Model used herein, allows for estimation of latent cognitive processes underlying observable behavioral responses, offering nuanced insights into decision-making and attentional dynamics beyond traditional behavioral measures alone.

To examine processes that may occur when socially salient distractors compete for attentional resources, in the first part of the project (Study 1; $N = 52$), we employed the dot-probe task, which is considered a gold standard in attentional bias research. Contrary to expectations, lonely individuals did not show increased vigilance to social stimuli during the task. This effect was consistently observed across standard response outcomes (response times), EEG derived markers of neural response to threat ($n2pc$), and DDM-derived indicators of perceptual engagement with threat distractors (t_0). At the same time, DDM analysis of the processes related to the efficiency of the information accumulation revealed difficulties in perceptual decision making among lonely compared to nonlonely individuals.

To assess whether loneliness is associated with increased affective response to social threat and potential difficulties in emotion regulation, Study 2 ($N = 150$) combined passive viewing and cognitive reappraisal of negative social and nonsocial images, with simultaneous EEG and electrodermal activity recordings. Lonely individuals showed increased P300 amplitude differences in response to negative vs

neutral social scenes, indicative of enhanced evaluative engagement. However, none of the ERP components typically associated with early attentional hypervigilance (P1, N1) or sustained affective processing (LPP) showed any differences between lonely and nonlonely individuals. Similarly, no group differences were observed in physiological arousal as indexed by skin conductance. Notably, subjective reports diverged from neural indices: lonely individuals rated negative scenes as less arousing and reported lower reappraisal success, revealing a dissociation between internal affective responses and conscious emotional experience, thus suggesting a possible reduction of emotional self-awareness among lonely individuals.

Finally, given the discrepancies between the levels of analysis observed in Study 1 and Study 2, the final part of the project (N = 271) examined how loneliness relates to both biases and abilities in understanding social situations. Participants completed a broad set of tasks measuring explicit social-cognitive capacity (e.g., emotion recognition, mental state inference) and social-cognitive bias (e.g., tendency to interpret ambiguous situations negatively). Outcomes from the explicit measures were combined with DDM-derived indicators of decision-making efficiency and early-stage perceptual processing from a dot-probe task to examine the association between overt and covert markers of social information processing in lonely individuals. Results showed that reduced decision-making efficiency was associated with objective social isolation, and this relationship was mediated by lower social cognitive capacity. In contrast, loneliness was linked to faster early-stage processing of social information, but this effect was suppressed by a high level of social cognitive bias in lonely individuals when threatening stimuli were present.

Taken together, the results provide no evidence for increased social threat vigilance in loneliness, as none of the main neurophysiological (P1/N1, N2pc, LPP) or computational (t_0) markers of vigilance have shown a positive association with loneliness. At the same time, the contrasting, albeit small, effects were found for objective (P300) and subjective (arousal ratings) markers of social threat evaluation. Finally, further investigation of the covert processes associated with attentional engagement with threats has revealed that contrasting effects may be context-dependent and further impacted by high-level social cognitive biases found in lonely individuals. Similarly, despite the theoretical formulations suggesting decreased cognitive control in lonely individuals, we have found no specific association between loneliness and objective markers of decreased inhibitory control or of top-down emotion regulation of affective response. The key conclusion is that loneliness is linked to abnormalities in later stages of social information processing, particularly in interpretive and evaluative mechanisms, which lead to observed discrepancies between objective outcomes and self-reports in lonely individuals. By shifting focus from hypervigilant threat detection to biased meaning-making and reduced emotional self-awareness, the present thesis offers a more nuanced perspective on loneliness and suggests novel targets for intervention.

Keywords: Loneliness, Hypervigilance, Affective Response, Inhibitory Control, Emotion Regulation, Social Cognitive Capacity, Social Cognitive Bias

Streszczenie

Samotność — definiowana jako subiektywne poczucie niewystarczających relacji społecznych — wiąże się ze znacznym ryzykiem problemów zdrowotnych, zarówno psychicznych, jak i somatycznych, a także z podwyższonym ryzykiem przedwczesnej śmierci. Modele poznawcze zakładają, że samotność nasila oddolną czujność wobec bodźców społecznych, co może pełnić adaptacyjną funkcję, sprzyjającą ponownej socjalizacji. Jednakże zwiększona czujność może prowadzić do nadreaktywnej reakcji na zagrożenia społeczne, nasilając negatywne emocje oraz sprzyjając tendencyjnym interpretacjom otoczenia społecznego. Reakcje te z kolei mogą wyczerpywać zdolność do odgórnej regulacji, co potencjalnie wzmacnia negatywne oceny sytuacji społecznych. Pomimo solidnych podstaw teoretycznych, dotychczasowe dowody opierają się głównie na danych samoopisowych, dostarczając ograniczonych informacji na temat przetwarzania bodźców społecznych w czasie rzeczywistym.

Aby wypełnić tę lukę badawczą, w cyklu badawczym zweryfikowano następujące hipotezy: (1) czy samotność wiąże się ze zwiększonymi oddolnymi reakcjami na zagrożenia społeczne — przejawiającymi się w nasilonym automatycznym ukierunkowaniu uwagi oraz zwiększonych reakcjach afektywnych na poziomie fizjologicznym; oraz (2) czy samotność wiąże się z osłabioną odgórną kontrolą regulacyjną podczas przetwarzania zagrożeń społecznych — przejawiającą się w obniżonej zdolności do utrzymania uwagi na bieżącym zadaniu, hamowania automatycznych reakcji oraz skutecznej regulacji emocji w obliczu zagrożeń społecznych. W ramach trzech badań zweryfikowano hipotezy dotyczące tych mechanizmów, wykorzystując metody behawioralne i samoopisowe, uzupełnione o techniki umożliwiające szczegółową analizę dynamiki przetwarzania bodźców społecznych — elektroencefalografię (EEG/ERP) oraz modelowanie obliczeniowe. Pomiar EEG/ERP umożliwia śledzenie aktywności neuronalnej w czasie rzeczywistym i dostarcza precyzyjnych informacji o kolejnych etapach przetwarzania bodźców społecznych. Modelowanie obliczeniowe, w szczególności zastosowany tu model dryfu-dyfuzji (DDM), pozwala na estymację utajonych procesów poznawczych leżących u podstaw obserwowanych reakcji behawioralnych, dostarczając wglądu w procesy decyzyjne i uwagowe wykraczające poza klasyczne wskaźniki behawioralne.

W celu zbadania procesów aktywujących się w sytuacjach, gdy społeczne dystraktory konkurują o zasoby uwagowe, w pierwszej części projektu (Badanie 1; N = 52) zastosowano zadanie dot-probe, uznawane za złoty standard w badaniach selektywną uwagą. Wbrew oczekiwaniom osoby samotne nie wykazywały zwiększonej czujności wobec bodźców społecznych w tym zadaniu. Brak tego efektu

konsekwentnie odnotowano zarówno w klasycznych miarach behawioralnych (czasy reakcji), wskaźnikach neuronalnych EEG reakcji na bodźce zagrażające (n2pc), jak i w parametrach modelu DDM opisujących wczesne zaangażowanie percepcyjne w obecności dystraktorów zagrażających (t_0). Jednocześnie analiza DDM wykazała, że osoby samotne podejmowały decyzje percepcyjne mniej efektywnie niż osoby niesamotne.

W celu zweryfikowania, czy samotność wiąże się ze zwiększoną reakcją afektywną na zagrożenia społeczne oraz potencjalnymi trudnościami w regulacji emocji, Badanie 2 (N = 150) łączyło pasywną ekspozycję oraz poznawczą reinterpretację negatywnych obrazów społecznych i niespołecznych, przy równoczesnym zapisie EEG oraz aktywności elektrodermalnej. U osób samotnych odnotowano większą różnicę amplitudy komponentu P300 między negatywnymi a neutralnymi bodźcami społecznymi, co wskazuje na silniejsze zaangażowanie w ocenę znaczenia bodźców. Natomiast żaden z komponentów ERP typowo związanych z wczesną czujnością uwagową (P1, N1) ani z utrzymującym się podtrzymywaniem uwagi (LPP) nie różnicował osób samotnych i niesamotnych. Podobnie, nie zaobserwowano różnic w pobudzeniu fizjologicznym mierzonym przewodnictwem skóry. Wystąpiła natomiast rozbieżność między wskaźnikami neuronalnymi a samoopisowymi: osoby samotne oceniały negatywne sceny społeczne jako mniej pobudzające oraz raportowały mniejszy sukces w regulacji emocji, co wskazuje na dysonans między fizjologiczną i świadomą reakcją emocjonalną, sugerując ograniczony wgląd we własne reakcje emocjonalne u osób samotnych.

Wobec niejednoznacznych wyników uzyskanych w Badaniach 1 i 2, końcowa część projektu (N = 271) badała relacje między samotnością a zdolnościami adekwatnej oceny i interpretacji sytuacji społecznych oraz tendencjami do ich negatywnego wartościowania. Uczestnicy wykonali szeroki zestaw zadań mierzących explicite zdolności społeczno-poznawcze (np. rozpoznawanie emocji, teoria umysłu) oraz tendencyjność społeczno-poznawczą (np. skłonność do negatywnej interpretacji sytuacji niejednoznacznych). Wyniki pomiarów explicite zestawiono ze wskaźnikami efektywności decyzyjnej oraz wczesnego przetwarzania percepcyjnego (DDM) uzyskanymi w zadaniu dot-probe, w celu zbadania relacji między jawnymi i utajonymi wskaźnikami przetwarzania informacji społecznych u osób samotnych. Wyniki wykazały, że obniżona efektywność decyzyjna była powiązana z obiektywną izolacją społeczną, przy czym związek ten był mediowany przez niższy poziom zdolności społeczno-poznawczych. Natomiast samotność wiązała się z szybszym wczesnym przetwarzaniem informacji społecznych, jednak efekt ten był tłumiony przez przeciwny wpływ nasilonej tendencyjności społeczno-poznawczej u osób samotnych w obecności bodźców zagrażających.

Podsumowując, wyniki nie dostarczają dowodów na zwiększoną czujność na zagrożenia społeczne u osób samotnych, gdyż żaden z głównych wskaźników neurofizjologicznych (P1/N1, N2pc, LPP) ani obliczeniowych (t_0) nie wykazał pozytywnego związku z samotnością. Jednocześnie

odnotowano niewielkie, lecz przeciwstawne efekty na poziomie obiektywnych (P300) i subiektywnych (oceny pobudzenia) wskaźników ewaluacji zagrożeń społecznych. Dalsza analiza utajonych procesów przetwarzania informacji społecznych ujawniła, że efekty te mogą być zależne od kontekstu oraz modyfikowane przez wyższe poziomy tendencyjności społeczno-poznawczej u osób samotnych. Ponadto, wbrew hipotezom, nie stwierdzono specyficznych związków między samotnością a obiektywnymi wskaźnikami kontroli reakcji automatycznych ani efektywności regulacji emocji. Kluczowym wnioskiem pracy jest to, że u osób samotnych przetwarzanie informacji społecznych wiąże się przede wszystkim z zaburzeniami mechanizmów interpretacyjnych, a nie ze zwiększoną czujnością na zagrożenia społeczne, co odzwierciedlają rozbieżności pomiędzy wynikami obiektywnymi i samoopisowymi. Niniejsza rozprawa proponuje bardziej zniuansowaną perspektywę, przesuwając akcent z wczesnych procesów percepcyjnych i uwagowych w stronę tendencyjnego nadawania znaczenia informacjom społecznym oraz ograniczonego wglądu w przeżywane stany emocjonalne, wskazując jednocześnie potencjalne nowe cele interwencyjne.

Słowa kluczowe: Samotność, Hiperczułość, Reakcja afektywna, Hamowanie reakcji, Regulacja emocji, Zdolności społeczno-poznawcze, Tendencje społeczno-poznawcze

Introduction

Loneliness—also referred to as perceived social isolation (PSI)—is the subjective experience that one’s social relationships are insufficient or unsatisfying (Perlman & Peplau 1981). It is conceptually distinct from objective social isolation, which refers to the actual number or frequency of social contacts. Although the two constructs are moderately correlated, loneliness reflects a unique psychological dimension of social disconnection (Cacioppo and Cacioppo 2018a). Recent large-scale data underscore the growing prevalence and significance of loneliness: an EU-wide survey found that 13% of Europeans felt lonely “most or all of the time,” and 35% at least some of the time (Berlingieri et al. 2023). In the United States, the 2023 Surgeon General’s Advisory described loneliness as a public health threat comparable in scale to smoking or obesity (General US Surgeon, 2023). These concerns are supported by the epidemiological evidence linking loneliness and social isolation to substantially elevated risks for all-cause mortality—by as much as 30%, according to some estimates (Holt-Lunstad et al. 2015; Wang et al. 2023)—as well as to increased risk of depression, sleep disturbances, cognitive decline, and impaired immune function (General US Surgeon, 2023).

Cognitive Models of Loneliness

Given the scale and consequences of loneliness for physical and mental health, explaining the mechanisms through which it emerges and persists has become an important focus for psychological science. Cognitive models seek to uncover how loneliness shapes the perception, interpretation, and regulation of social information and how these cognitive mechanisms may underlie negative psychological and physiological effects observed in lonely individuals.

Among the theoretical models proposed to explain how loneliness emerges and persists, the Evolutionary Theory of Loneliness (ETL) stands out as the most comprehensive—primarily because it formulates a broad set of physiological predictions, including those concerning stress reactivity, immune function, and cognitive performance (Cacioppo and Cacioppo 2018b). According to this framework, loneliness has evolved as an aversive, hunger-like state that motivates individuals to seek reconnection when perceived social support is lacking. Perceived social isolation is thought to increase bottom-up vigilance toward social cues in ways that promote reconnection (Cacioppo et al. 2014). However, since evolutionary pressures also favor self-preservation, this vigilance may at times become biased toward detecting threats, especially in ambiguous situations. As a result, loneliness may lead to a general sense of mistrust and social withdrawal. Moreover, ETL predicts that loneliness may impair self-regulatory functioning, as increased cognitive monitoring for social threats depletes resources needed for higher-order processes like emotion regulation or impulse control. Although ETL offers a broad explanatory framework, it does not clearly specify how such mechanisms manifest at the level of specific

cognitive operations or behavioral tasks.

Extending prior theoretical accounts, Spithoven et al. (2017) applied the Social Information Processing model stemming from studies of aggression in children (Crick and Dodge 1994) to interpret the cognitive mechanisms through which loneliness may be maintained. In this view, loneliness is associated with a so-called negativity bias in social information processing—a tendency to interpret the social world in a more threatening or self-defeating way. The negativity bias has been proposed to operate across multiple cognitive levels, including attentional allocation, encoding, interpretation, and memory. Importantly, such a view is supported by self-report and vignette-based studies measuring tendencies for specific attributions, which relatively consistently show a negativity bias at higher levels of social information processing, such as negative self- and other-evaluations, pessimistic social attributions, and heightened expectations of rejection. However, as noted by Spithoven et al. (2017), evidence from studies assessing the relationship between loneliness and objective markers of perceptual, emotional, or regulatory processes remains limited and inconclusive.

Complementing prior theoretical frameworks, Wong et al. (2022) proposed that loneliness may lead to sustained up-regulation of cognitive control mechanisms in order to manage heightened attentional biases toward socioaffective cues. Over time, this prolonged effort could drain cognitive resources and contribute to affective dysregulation. This model was based on the findings from a meta-analysis of neuroimaging studies, which identified an association between loneliness and upregulation of brain regions such as the striatum, insula, and frontal areas, which are involved in affective and cognitive processing. Authors suggest that co-activation of such regions with networks implicated in top-down control may lead to overrecruitment of cognitive control systems in response to emotionally salient social stimuli in lonely individuals.

Collectively, the reviewed theoretical accounts converge on the notion that loneliness is broadly associated with heightened bottom-up response to social threat, alongside disrupted top-down regulation of threat-related processing; these two interrelated domains form the conceptual backbone of the present work. The following chapters will critically review empirical findings related to bottom-up and top-down cognitive mechanisms in loneliness.

Bottom-up response to social stimuli in loneliness.

Bottom-up processes refer to automatic, reflexive mechanisms that are triggered directly by environmental cues, operating independently of current goals (Satpute and Lieberman 2006). In the context of social functioning, such processes are responsible for the detection of socially relevant cues and the initial assignment of affective significance. In loneliness research, bottom-up responses to social threat have been conceptualized and operationalized in diverse ways across studies. Here, I focus on

three partially overlapping lines of research that examine attentional vigilance to threats, generation of affective response to socioaffective stimuli, and effectiveness of processing of social cues.

Attentional Vigilance to social stimuli

Traditionally, “hypervigilance” is defined with regard to the early perceptual and attentional processes associated with preferential allocation of cognitive resources toward threatening stimuli (Richards et al. 2014). Such an approach is often utilized in the research on vigilance toward threats in anxiety disorders (Pergamin-Hight et al. 2015), including social threat vigilance in social anxiety. Spatial cueing tasks, such as the dot-probe, are commonly used to assess hypervigilance. In these tasks, faster responses to targets appearing in the same location as previously shown threatening stimuli (e.g. angry face) are taken as evidence of bottom-up attentional capture. However, this approach has rarely been applied to loneliness. To date, only one study (Wei et al. 2020) has used a classic RT-based dot-probe task in this context, reporting that loneliness was associated with faster responses to sad (but not fearful) faces. A complementary line of research has used eye-tracking to measure gaze patterns in response to social threat. Some studies report that lonely individuals spend more time attending to cues related to social exclusion or rejection (Qualter et al. 2013; Bangee et al. 2014). However, findings are mixed: other studies found no consistent attentional preference for negative facial expressions or general social threat (Bangee and Qualter 2018; Lodder et al. 2015).

In addition to eye-tracking, attentional responses to socially salient stimuli have also been examined using electroencephalography (EEG)—a technique that allows for real-time monitoring of neural activity and is particularly useful for identifying early-stage processing differences. In Cacioppo et al. (2015), 70 individuals completed a Stroop task involving negative words with social or nonsocial content; lonely individuals showed distinctive neural activity for social and nonsocial stimuli at the earlier stages of stimulus processing than nonlonely individuals. Du et al. (2022) extended these findings in a categorization task, reporting faster neural responses to angry faces in lonely individuals compared to nonsocial control images. However, none of these studies employed paradigms specifically designed to measure selective attention, as participants were not required to process or prioritize competing stimuli—a core feature of tasks commonly used to investigate attentional mechanisms in clinical populations, such as various forms of anxiety (Pergamin-Hight et al. 2015).

Automatic affective response generation

Another line of studies has examined bottom-up affective responses to negative social stimuli in loneliness. This approach has a long-standing tradition in social and affective neuroscience and typically involves the presentation of standardized image sets, such as the International Affective Picture System

(Bradley and Lang 2017), which contains emotionally evocative scenes normed for valence and arousal. However, stimuli used in such studies often evoke a blend of various basic emotions - most commonly fear, disgust, and sadness—rather than any specific type of response (e.g., threat response). In the context of loneliness, evidence on bottom-up affective responses comes primarily from fMRI studies. Cacioppo et al. (2009) reported that, among female students ($n = 23$), those with higher loneliness scores showed greater arousal to unpleasant social scenes and increased activation in the visual cortex, along with reduced activity in the ventral striatum and temporoparietal junction, compared to students with lower loneliness scores. However, in a subsequent well-powered ($n=99$) neuroimaging study, D’Agostino et al. (2019) found no differences in either self-reported affective responses or neural activation patterns between lonely and nonlonely participants. Similarly, Wiśniewska et al. (2025) reported nonspecific differences in fusiform activity between lonely and nonlonely individuals but no group differences in activity within core affective and social brain regions in response to negative or positive social stimuli between lonely and nonlonely individuals. Notably, the neural response patterns observed in lonely individuals do not resemble the typical profile of heightened affective reactivity found in clinical populations such as social anxiety disorder or major depressive disorder, where elevated subjective arousal elicited by social negative stimuli is accompanied by elevated amygdala and insula activation (Kanske and Kotz 2012; Groenewold et al. 2013; Etkin and Wager 2007).

Processing of social cues

As noted by Spithoven et al. (2017) in their SIP model of loneliness, social threat hypervigilance should be reflected by the increased sensitivity to specific social cues. Thus, studies investigating processes associated with basic social perception and emotion recognition should document enhanced accuracy in detecting socially threatening cues, particularly anger or fear-related signals. In line with this notion, several studies suggest that lonely individuals may show heightened sensitivity in detecting and recognizing negative facial expressions (Lodder et al. 2016; Vanhalst et al. 2017; Di Tella et al. 2023). Other findings, however, indicate decreased emotion detection in lonely individuals (Morningstar et al. 2020; Cheeta et al. 2021; Zysberg 2012). Finally, several studies found no association between loneliness and emotion recognition (Kanai et al. 2012; Knowles et al. 2015; Kiyak et al. 2024). Okruszek et al. (2021) used a comprehensive battery of tasks measuring social cognitive capacity, found no relationship between loneliness and lower-level social cue processing, even despite the fact that such a relationship was found for objective social isolation. The latter finding supports previous findings which suggest that objective social isolation correlates with deficits across domains of nonsocial cognitive capacity (Evans et al. 2019), and as such, its effects should be carefully separated from those which can actually be attributed to loneliness.

Top-Down cognitive processes during social information processing in loneliness

Top-down processes refer to cognitive mechanisms that support the regulation of perception, attention, and behavior in line with internal goals (Gaspelin and Luck 2018). While often described as deliberate or strategic, top-down processes do not necessarily require conscious awareness. According to theoretical accounts of loneliness, chronic perceived social isolation may impair self-regulatory capacity, leading to difficulties in overriding automatic responses and adjusting behavior to situational demands (Cacioppo et al. 2014). Several top-down processes have been emphasized by cognitive models of loneliness and examined in the studies: inhibitory control, cognitive emotion regulation, and mental state attribution.

Inhibitory Control

Inhibitory control refers to the ability to flexibly shift attention, inhibit prepotent responses, and maintain goal-relevant representations in the presence of distraction (Miller and Cohen 2001). Navigating social environments often demands the ability to override automatic reactions or ignore irrelevant social cues - capacities that, in line with cognitive models, may be compromised in loneliness due to increased bottom-up response to threat. While a systematic review by Boss et al. (2015) concluded that loneliness predicts poorer executive functioning in older adults, including deficits in working memory and cognitive control, evidence from performance-based studies in the general population remains scarce. Two studies indicated reduced inhibitory control in lonely individuals. In a dichotic listening task, lonely participants showed reduced accuracy when instructed to attend to the non-dominant ear, suggesting weaker attentional control under conflicting input conditions in this group (Cacioppo et al. 2000). A subsequent study using an auditory Stroop task, lonely individuals were more distracted than non-lonely individuals by incongruent emotional prosody, particularly when processing socially relevant words (Shin and Kim 2019). However, another two studies have reported null results with regard to the association between loneliness and inhibitory control: Cacioppo et al. (2015) found no group differences in response times in visual emotional Stroop task, and Bocincova et al. (2019) observed no association between loneliness and behavioral or neural measures of cognitive control in a flanker task.

Cognitive Emotion Regulation

Cognitive emotion regulation refers to the deliberate use of cognitive strategies, such as reappraisal or suppression, to modulate the intensity, duration, or expression of emotional responses. It plays a central role in adaptive functioning, enabling individuals to maintain emotional balance in the face of everyday challenges. Cognitive emotion regulation is closely linked to cognitive control, as it

requires monitoring emotions, inhibiting automatic responses, and flexibly shifting perspective to align behavior with goals. A recent meta-analysis by Patrichi et al. (2024), synthesizing 61 studies with over 40,000 participants, found that lonely individuals reported greater use of maladaptive emotion regulation strategies such as rumination and suppression, alongside more general difficulty in regulating emotions. Conversely, Patrichi et al. (2024) also reported less frequent use of adaptive strategies like reappraisal and distraction, and lower perceived regulatory abilities in more lonely individuals. However, although there is robust evidence that cognitive regulation strategies—particularly reappraisal—are reflected in neurophysiological markers such as the Late Positive Potential (Buhle et al. 2013), these findings are based exclusively on self-report measures; no studies to date have directly assessed the effectiveness of emotion regulation in lonely individuals using behavioral or physiological outcomes. Moreover, it remains unclear whether these difficulties are specific to emotionally charged social contexts or reflect broader impairments in emotion regulation.

Mental state attribution

Mental state attribution refers to the processes by which individuals infer others' internal states—such as beliefs, intentions, desires, or emotions—based on observed behavior. On the one hand, mental state attribution can be understood as a capacity—that is, the general ability to accurately represent and reason about other people's mental states (Roberts and Pinkham 2013). This form of attribution is typically assessed using neutral, third-person tasks in which participants interpret the intentions or emotions of unfamiliar individuals in decontextualized scenarios. In such contexts, the participant adopts the role of an uninvolved observer, which promotes more objective judgments. On the other hand, mental state attribution should also be considered with regard to specific tendencies or biases observed while inferring others' intentions, mostly with regard to a self-referential tendency to interpret ambiguous or neutral social cues in a negative or threatening light (Roberts and Pinkham 2013). This interpretive dimension is typically assessed using tasks that place participants in hypothetical, personally salient social situations (e.g., being excluded or misunderstood) and measure the degree to which they infer hostile intent or negative affect in others' actions. Multiple studies found that higher loneliness scores correlated with a greater propensity to attribute hostile intentions in ambiguous peer-related scenarios (Qualter et al. 2013; Okruszek et al. 2021; Skoko et al. 2025; Nombro et al. 2022; Lau et al. 2021). On the other hand, De Lillo et al. (2022) found no association between loneliness and performance on tasks assessing theory of mind and perspective-taking in older adults after adjusting for age. Likewise, Okruszek et al. (2021) found no significant relationship between loneliness and the ability to infer mental states. Taken together, these findings suggest that loneliness may not be associated with

impairments in the capacity to accurately infer others' mental states, but rather with systematic biases in the interpretation of such information—distortions that occur despite preserved inferential abilities.

Disentangling Bottom-Up and Top-Down Processes during social information processing

Although the distinction between bottom-up and top-down processes is conceptually useful—referring broadly to reflexive versus goal-directed mechanisms—it is not a strict or mutually exclusive dichotomy. As such, the division should be understood as a heuristic framework rather than a literal separation of underlying systems, which usually show a high level of interdependence and interrelatedness and have a continuous rather than dichotomous nature. Within this framework, we map specific cognitive operations onto the bottom-up or top-down dimension based on their primary drivers (e.g., external input vs. internal goals), while acknowledging that many processes involve elements of both. However, even when adopting this heuristic framework, empirically separating the two types of processes remains problematic, as they often operate in parallel and continuously interact. For example, seeing an angry facial expression automatically triggers bottom-up processing, such as rapid orienting and physiological arousal. The speed and nature of the behavioral response will partly depend on the intensity of this initial reaction. At the same time, reaction is also shaped by top-down processes such as expectations, current goals, or the ability to inhibit or reinterpret the initial impulse—making it difficult to separate the relative contribution of each component based on behavioral responses alone (Schweinberger and Neumann 2016; McMains and Kastner 2011). Two methodological approaches may be particularly useful in disentangling this dynamic, i.e. use of EEG event-related potentials (ERPs), which allows for a fine-grained analysis of the temporal unfolding of neural processes, and computational modelling of overt behavioral responses, which can decompose observed behavior into latent cognitive components. Each of these approaches is discussed in the sections below.

EEG Event Related Potentials

EEG, and in particular event-related potentials (ERPs), offer a valuable methodological approach for disentangling the temporal dynamics of cognitive processing. Unlike behavioral measures such as reaction time, decision accuracy, or ratings, which typically yield a single data point per trial, event-related potentials (ERPs) allow researchers to track neural activity in real time and map it onto different cognitive processes as they unfold during stimulus processing. These markers include early components related to sensory encoding (e.g., P1, N1) and attentional selection (e.g., N2pc), as well as activity observed during the later stages of the stimuli processing, which may be linked to initial cognitive evaluation (e.g., P3) or attention maintenance (Late Positive Potential [LPP]). The LPP, in particular, has received considerable attention in affective science, where it is conceptualized as a neural

index of stimulus significance, reflecting the sustained engagement of motivational systems and the ongoing allocation of attentional resources toward emotionally salient information (Hajcak and Foti 2020). Moreover, the LPP exhibits excellent psychometric properties, including high internal consistency and stability, even when derived from a relatively small number of trials (Moran et al. 2013). Numerous studies have employed ERP methodology to characterize stage-specific differences in information processing across both general and clinical populations (Hajcak et al. 2010; Lu et al. 2025; Donoghue and Voytek 2022). Figure 1 illustrates the temporal cascade of ERP components commonly observed in studies of attentional bias, highlighting group differences at both early and late processing stages. This temporal dissociation is central to distinguishing bottom-up automatic mechanisms from later evaluative or regulatory processes, and makes ERPs a particularly valuable tool in research on social-affective functioning.

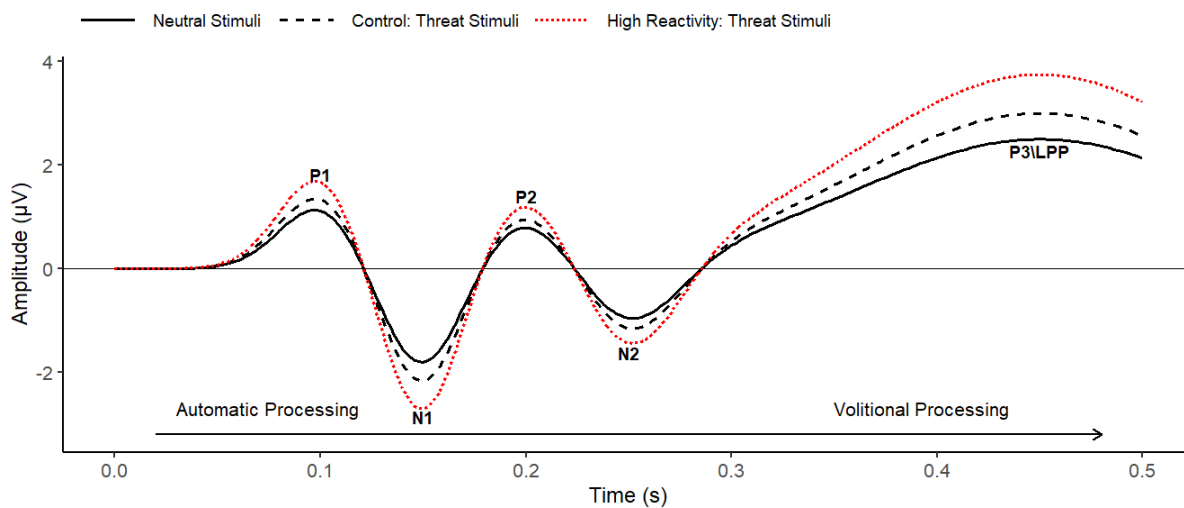


Figure 1. Illustrative model of the temporal dynamics of threat-related attentional bias, adapted from the Neural Chronometry Model (adapted from: Gupta et al. 2019). Attentional bias toward threatening or emotionally salient stimuli may manifest through distinct temporal stages. Early ERP components (P1, N1, P2, N2) reflect rapid, automatic, and largely preconscious orienting to salient cues, often linked to heightened vigilance. In contrast, later components (P300 and LPP) are associated with evaluative or controlled processes, such as sustained engagement or difficulty disengaging from emotional stimuli.

Computational Modeling

Another approach to disentangle bottom-up and top-down processes involves fitting formal cognitive models to behavioral data. A widely used example is the Drift Diffusion Model (DDM; Ratcliff and McKoon 2008), which models binary decisions as the accumulation of noisy evidence over time until a decision threshold is reached. Importantly, DDM decomposes total response time into decision-related and nondecision components—separating the decision process from peripheral stages related to non-decision processes like sensory encoding and motor execution. In its most basic form, the model dissociates the parameter associated with the speed and quality of evidence accumulation (drift rate - v), from the pre- and post-decisional processes not directly associated with evidence accumulation, e.g.,

impact of the perceptual processing of threat distractors on decision process (nondecision time - t_0). As presented in Figure 2, DDM provides insight into the latent cognitive mechanisms underlying task performance. Notably, t_0 has been linked to early attentional processing, including functional connectivity in control and attentional networks (Price et al. 2019) and N2 ERP latency (Nunez et al. 2017; Nunez et al. 2019), supporting its interpretation as an index of early-stage attentional bias. In contrast, drift rate is considered a robust indicator of task engagement and the quality of perceptual decision-making (Voss et al. 2004), making it a suitable candidate for quantifying top-down control processes.

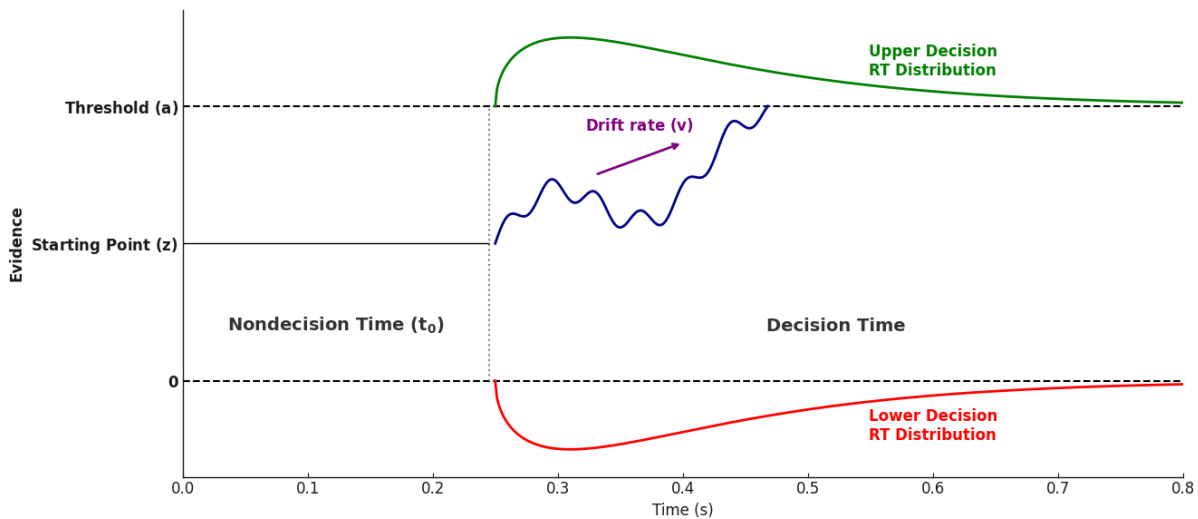


Figure 2. This figure provides a simplified illustration of the Drift Diffusion Model, which describes binary forced-choice decisions as a process of evidence accumulation over time. In each trial, the decision process begins after a non-decision time t_0 (grey vertical line), during which no decision-related computation and motor response occur. From a starting point (z), evidence (blue trajectory) accumulates with a mean rate determined by the drift rate (v) until it reaches one of two decision boundaries (dashed lines), corresponding to alternative responses. The starting point reflects an a priori bias toward one of the decisions, while the distance between the boundaries is determined by the threshold parameter (a), which reflects the amount of evidence required to make a decision; higher values imply more cautious decision-making. Repeating this process across trials yields reaction time distributions for upper (green) and lower (red) decisions.

Research goals and hypotheses

Current conceptualizations suggest that loneliness may influence both bottom-up and top-down processes observed in response to social stimuli. While existing studies have examined this possibility, the available evidence is highly heterogeneous, differing widely in methodological design, measurement approaches, and analytic focus. Many studies assess distinct stages or components of processing in isolation, making it difficult to determine which specific mechanisms are most reliably associated with loneliness.

To address this gap, the present research program investigates how loneliness relates to both bottom-up and top-down processes in social information processing. This is achieved through a multi-level approach encompassing self-report, behavioral performance, neurophysiological measures (EEG), and computational modeling. Rather than focusing on isolated trajectories, the aim is to

characterize the functional profile of social information processing in lonely individuals across multiple levels of analysis. The core research questions guiding this investigation are outlined below.

RQ1: Is loneliness linked to enhanced bottom-up attentional vigilance to socially threatening distractors during a perceptual decision-making task?

Although prior research tentatively suggests heightened attentional vigilance in loneliness, no studies have directly examined selective attention to social threats. Tasks that require participants to make speeded judgments while ignoring irrelevant information offer a way to test whether socially threatening cues automatically capture attention. I predict that higher levels of loneliness will be associated with stronger attentional capture by social threat cues, as reflected by: (H1a) faster response times, (H1b) enhanced N2pc amplitudes, and (H1c) shorter Drift Diffusion Model-derived nondecision times (t_0) in the dot-probe task.

RQ2: Is loneliness linked to decreased inhibitory control in a perceptual decision-making task elicited by social distractors?

Successfully maintaining focus on the task in complex contexts depends on the ability to suppress interference and flexibly allocate attention. Thus, increased attentional vigilance to social threats may also interfere with cognitive control during perceptual decision making, particularly under cognitively demanding circumstances (e.g., when the task demands implementation of inhibitory control). I predict that higher levels of loneliness will be associated with decreased ability to implement inhibitory control, as indicated by (H2a) longer reaction times and (H2b) lower drift rates (v) during the inhibitory trials of the dot-probe task.

RQ3: Is loneliness linked to bottom-up affective response to socially negative stimuli?

Unlike attention tasks, in which threat-related stimuli are peripheral, tasks involving passive viewing of emotionally negative images require participants to focus directly on the presented socioaffective content. This approach allows for the direct assessment of bottom-up responses to such input at both the subjective and physiological levels. I predict that higher levels of loneliness will be associated with stronger subjective arousal and more negative valence ratings (H3a), as well as increased early (P1, N1, EPN; H3b) and middle-stage (P3, H3c) and late, sustained (LPP, H3d) ERP components in response to negative versus neutral social images.

RQ4: Is loneliness linked to the ability to regulate emotional responses to socially negative stimuli?

Prior self-report studies indicate that lonely individuals report greater difficulties in emotion regulation.

Experimental paradigms requiring participants to reappraise negative stimuli offer a way to assess regulatory ability beyond self-report. Previous studies have reliably shown that implementation of the top-down emotion regulation strategies decreases subjective arousal ratings and decreases LPP in response to affective stimuli (Kennedy and Montreuil 2020; Hajcak et al. 2010; Thiruchselvam et al. 2011). I predict that loneliness will be linked to decreased impact of cognitive reappraisal on affective response to negative social stimuli, as reflected by the smaller change in arousal and valence ratings following reappraisal (H4a), as well as reduced downregulation of P300 and LPP amplitudes in response to reappraised social negative images (H4b) in more lonely individuals.

RQ5: Is increased attentional vigilance to socially salient information linked to social cognitive bias in lonely individuals?

Lonely individuals are often thought to interpret ambiguous social cues in an overly negative or self-referential way. However, it remains unclear whether such bias is linked to early-stage processing of socially relevant input. While prior research has demonstrated the presence of both low level perceptual and high level interpretative biases, the association between these two levels of biased processing remains poorly understood. According to cognitive models of loneliness, attentional vigilance to social threats should foster the development of interpretative biases by increasing the salience of negative social information. I predict (H5) that the association between loneliness and early-stage processing speed (t_0) in response to social stimuli will be mediated by social cognitive bias.

RQ6: Is inhibitory control of responses to socially salient information linked to social cognitive capacity in lonely individuals?

While loneliness is frequently associated with distorted interpretations of social information, evidence regarding its link to actual social-cognitive abilities remains mixed. Prior research suggests that reduced detection of social cues is associated with objective—but not perceived—social isolation (Okruszek et al., 2021). This raises the question of whether the ability to sustain task engagement in socially distracting contexts reflects differences in social-cognitive capacity—and whether this, in turn, is uniquely linked to loneliness. I predict (H6) that the association between loneliness and top-down responses (v) to social stimuli will be mediated by social cognitive capacity.

Methods and Results

The empirical core of this dissertation comprises three studies, two of which have been published in peer-reviewed journals and one currently under review and available as a preprint. The target population in all three studies consisted of young adults aged 18–35. This age group was selected for two key reasons. First, most of the existing research on loneliness has focused on adolescents and older

adults, leaving young adulthood comparatively underexplored. Secondly, socioaffective functioning is shaped by developmental and neurobiological processes that differ across life stages. In adolescence, many regulatory and affective systems are still maturing, while in older age, cognitive and physiological decline may confound the effects of loneliness. Thus, studying young adults, who are beyond major developmental transitions but not yet affected by age-related changes, offers a unique opportunity to examine the impact of loneliness on cognition and emotion without developmental or degenerative confounds. Below is a summary of each part of the cycle.

Examining Vigilance to Social Threats in the Context of Perceptual Decision-Making

Introduction: Selective attentional vigilance to threat-related cues has been extensively studied in social anxiety, where it is often assessed using the dot-probe task. The aim of the first study was to apply this well-established approach to investigate whether similar patterns of increased selective attention to social threat emerge in lonely individuals (RQ1). To further examine how socially threatening distractors affect task performance under increased cognitive demand, the task was modified to include trials requiring inhibitory control (RQ2). At the same time, recognizing growing concerns about the limited psychometric validity of conventional behavioral indices derived from the dot-probe task, we incorporated two additional methods to strengthen the inference: EEG and computational modeling.

Methods: This study was conducted as part of a project funded by the National Science Centre, Poland (Grant No: 2019/35/B/HS6/00517, Principal Investigator: Łukasz Okruszek). Fifty-two right-handed adults aged 18–35 were recruited and divided into high-lonely and low-lonely groups ($n = 26$ per group) based on scoring in the top or bottom quartile of the Revised UCLA Loneliness Scale (R-UCLA). Participants completed a modified version of the dot-probe task using facial stimuli while EEG was recorded. Each trial began with the lateral presentation of a face pair (angry–neutral or neutral–neutral), followed by a target stimulus (a horizontal or vertical colon) appearing in the location of one of the faces. Participants were instructed to respond to the orientation of the target via keypress. The task included two independent manipulations: firstly, the target appeared either in the same location as the angry face (congruent), on the opposite side (incongruent), or followed the presentation of two neutral faces (baseline). This way, the congruence between the spatial positions of the angry faces and the target was manipulated to examine attentional bias toward threat. At short stimulus onset asynchronies (typically below 300 ms), faster responses are observed in the congruent condition. Secondly, the inhibitory condition manipulated the spatial compatibility of the response: the keypress (e.g., right) either matched the target's on-screen location (right) or was incongruent with it (left), thereby introducing the need to

inhibit a prepotent response, which typically results in longer response time. Details of the computational modelling, EEG preprocessing and ERP extraction are discussed in (Mąka et al. 2023).

Results: Contrary to our hypothesis (H1a), lonely individuals did not exhibit faster reaction times to targets appearing in the location of threatening stimuli. Further investigation revealed no differences measured by nondecision time (H1b) or N2pc amplitude (H1c). No evidence for increased selective attention in lonely individuals was found at any level of analysis. In contrast, although no overt differences in behavioral performance were observed (H2a), lonely individuals showed significantly lower drift rates (v) across all conditions (not only inhibitory trials), indicating a nonspecific reduction in decision-making efficiency. Exploratory analyses further revealed decreased drift rate variability (sv) in lonely participants, suggesting that the accumulation of evidence was also less stable across trials. As these effects were not confined to high-demand (inhibitory) trials, the pattern is broadly consistent with H2b, though it points to a more general performance decrement. Importantly, these effects were observed exclusively through the use of computational modeling and were not detectable using standard measures of task performance.

Discussion: The observed decrease in performance among lonely individuals appears nonspecific, as it was not modulated by task conditions designed to vary attentional and inhibitory demands. This suggests that the effect is not driven by increased inhibitory demand, as hypothesized. Instead, it may reflect reduced top-down maintenance of task goals in the presence of social distractors—even when the need for cognitive control is low. Due to the absence of a control condition involving nonsocial stimuli, the current design does not allow us to determine whether the observed effect is specific to social distraction or reflects a domain-general deficit. Nevertheless, these findings underscore the importance of going beyond surface-level metrics when investigating the cognitive consequences of loneliness.

Examining Responses to Socioaffective Stimuli During Automatic Processing and Top-Down Cognitive Reappraisal

Introduction: Study 2 examined whether loneliness is associated with increased bottom-up processing when participants directly view and evaluate emotionally salient stimuli (RQ3). Compared to Study 1, which presented social stimuli as distractors, this design allowed for a more explicit assessment of affective reactivity by placing emotionally negative stimuli at the center of attention. In addition, Study 2 aimed to test whether loneliness is linked to diminished emotion regulation ability—an association widely reported in self-report studies, but not previously tested using experimental paradigms (RQ4). Given that the lack of nonsocial stimuli was a substantial limitation of Study 1, both social and nonsocial

emotional images were included, enabling assessment of whether the observed effects are specific to the social domain or reflect broader affective differences.

Methods: This study was conducted as part of a project funded by the National Science Centre, Poland (Grant No: 2019/35/B/HS6/00517, PI: Łukasz Okruszek). One hundred fifty right-handed adults (aged 18–35) were recruited using quota sampling to ensure full coverage of the UCLA-R loneliness score distribution. The study consisted of two experimental sessions. In the first session, participants completed a Set-Shifting Task as a measure of cognitive control, included to test whether potential difficulties in emotion regulation among lonely individuals might stem from reduced top-down control, as suggested by findings from Study 1. During the second session, participants performed the tasks during which they viewed emotionally negative and neutral images, either social or nonsocial in content, while their EEG and Electrodermal Activity (EDA) were recorded. Participants were instructed to either passively watch or to decrease their affective response to pictures via cognitive reappraisal. After each trial, participants were asked to provide the arousal and valence ratings for the picture. To control for potential confounds, participants also completed questionnaires assessing depressive symptoms and social anxiety, which frequently co-occur with loneliness and are known to modulate affective responding.

Results: Hypothesis H3a, predicting increased subjective emotional reactivity in lonely individuals, was not supported: actually, more lonely participants reported decreased arousal difference between negative and neutral social images, indicating, contrary to our predictions, a reduction in reported affective intensity in lonely individuals. H3b and H3d, concerning early and late stage neural responses, was likewise not supported, as no association between loneliness and early ERP (P1/N1/EPN) or late (LPP) components was observed. In contrast, H3c was supported: higher loneliness was associated with greater P300 amplitude differences between negative and neutral social images during passive viewing ($r = 0.19$). This pattern indicates a dissociation between neural activation and subjective emotional experience in lonely individuals. Regarding reappraisal efficiency, differences in arousal ratings between reappraisal and passive viewing conditions showed that lonely individuals experienced smaller reductions in arousal following reappraisal of social negative stimuli, suggesting diminished regulatory success at the subjective level, consistent with H4a. However, no corresponding differences were observed in physiological markers, including EEG or skin conductance measures (H4b). Finally, exploratory analyses revealed no association between cognitive control (Set-Shifting Task) and loneliness. Moreover, further investigation of potential confounding effects revealed that controlling for social anxiety actually strengthened both neural and subjective associations with loneliness during passive viewing of negative vs neutral social images. The association between loneliness and enhanced P300 amplitudes increased to $\beta = 0.36$, exceeding typical effect sizes reported in personality neuroscience (average $r \approx .17$; Mar et al., 2013). A similar, although more modest, strengthening of the association was also observed for

self-reported arousal ratings, where the correlation became more negative after controlling for social anxiety.

Discussion: In contrast to predictions derived from the cognitive model of loneliness, the study did not reveal consistent evidence for heightened bottom-up affective responses to social threat. The only observed effect was specific to the P300 time window, suggesting that loneliness may amplify initial evaluative processing of emotionally salient social information without affecting later, sustained elaboration. Similarly, no objective impairments in emotion regulation were observed at the physiological level, as indicated by both electrophysiological and autonomic (skin conductance) markers during cognitive reappraisal. However, the most striking finding from this study lies in the dissociation between neural and subjective responses: lonely individuals reported blunted arousal to negative social stimuli and lower regulation success, yet these subjective reports did not align with their neural activation patterns. This discrepancy may point to reduced affective self-insight in loneliness—that is, a mismatch between internal emotional reactivity and consciously accessible experience.

Examining the Association Between Covert Markers of Social Information Processing and Overt Social Cognitive Capacity and Bias

Introduction: Loneliness has been linked to an increased tendency to interpret ambiguous social cues negatively. However, it has also been hypothesized that loneliness may alter the capacity to process socially relevant information. Prior findings on this issue have been mixed. Results from Study 1 and Study 2 echo this ambiguity. While Study 1 revealed reduced decision-making efficiency in lonely individuals, Study 2 found no objective impairments in emotion regulation or cognitive control, despite self-reported difficulties, suggesting possible distortions in self-perception rather than deficits in processing capacity per se. Discrepancies between subjective and objective responses to socioaffective stimuli observed in Study 2 have been further explored in the final part of the project, which investigated the association between loneliness and overt and covert social cognitive mechanisms. Therefore, to clarify these ambiguities, the final part of the project tested whether previously observed bottom-up and top-down differences in social threat processing linked to loneliness are differentially linked to distinct overt cognitive mechanisms: specifically, whether increased sensitivity to social threat is linked to social cognitive bias (RQ5), and whether difficulties in sustaining task engagement amid social distraction are linked to the reduced social-cognitive capacity (RQ6).

Methods: Study 3 was conducted as part of two research projects supported by the National Science Centre, Poland (Grant Nos: 2018/31/B/HS6/02848 and 2019/35/B/HS6/00517, PI: Łukasz Okruszek). Data from the 271 adults aged 18–35 collected during the behavioral assessment part of each project were pooled for the analysis. Each participant completed scales measuring loneliness (Revised UCLA Loneliness Scale) and objective social isolation (Lubben Social Network Scale) as well as a comprehensive battery of tasks capturing facial emotion recognition, sensitivity to social cues, and the ability to infer mental states (Pinkham et al. 2018). Furthermore, social cognitive bias was assessed using self-report questionnaires and vignettes probing for hostile attributions in ambiguous interpersonal scenarios. Finally, participants also completed a dot-probe task with a design nearly identical to that used in Study 1, except for one key modification: trials involving neutral-neutral and neutral-angry face pairs were presented in separate blocks. In the first block, only neutral-neutral pairs were shown, followed by a block consisting exclusively of neutral-angry trials. Structural equation models were used to replicate and extend the model proposed by Okruszek et al. (2021) by testing whether dot-probe-derived DDM parameters (v , t_0) predict perceived and objective social isolation, with these associations mediated by social cognitive bias and social cognitive capacity. Separate models were estimated for baseline (neutral faces) and threat (angry and neutral faces) conditions of the dot-probe task to capture condition-specific effects.

Results: We conceptually replicated the findings of Okruszek et al. (2021): social cognitive bias was associated with both perceived and objective social isolation, whereas social cognitive capacity was linked specifically to objective—but not perceived—isolation. The pattern of the observed results was more complicated than the one predicted by the H5. Firstly, nondecision time was negatively related to perceived loneliness under both baseline and threat conditions. Secondly, nondecision time was not associated with social-cognitive bias under baseline conditions; however, in the threat condition, a significant positive association emerged, indicating that higher levels of bias were linked to prolonged early-stage processing in response to social threat. In this condition, nondecision time also indirectly positively predicted higher perceived loneliness through its association with social-cognitive bias (H5 supported). However, this pattern reflects a suppression effect, as the direct and indirect paths linking nondecision time to loneliness had opposite signs. At the same time, drift rate was positively associated with social cognitive capacity and indirectly predicted lower levels of objective, but not perceived, isolation (H6 not supported). Additionally, in the baseline condition, drift rate was negatively associated with social-cognitive bias; however, no indirect effect on loneliness was observed.

Discussion: The results of the study support the notion that distinct cognitive mechanisms may underlie different pathways through which social cognitive bias is formed, which may have important implications for loneliness research. Specifically, two complementary routes linking covert social

information processing mechanisms and social cognitive bias were found: in neutral contexts, social cognitive bias was primarily linked to reduced information processing capacity, suggesting that interpretive distortions can emerge even in the absence of overt threat, potentially due to limited cognitive resources. In contrast, when socially threatening cues were present, social cognitive bias became more strongly associated with prolonged early perceptual processing, indicating a heightened engagement with socially threatening stimuli. In the context of loneliness, this pattern becomes particularly relevant. Lonely individuals consistently have faster early-stage processing, regardless of whether social threat cues were present. This may reflect a generally facilitated social stimulus processing. However, when threatening social cues are involved, this effect appears to be attenuated by social cognitive bias. In individuals prone to interpreting ambiguous social cues as hostile, often those with higher loneliness, early processing of social threat was slower, cancelling out the facilitation effects associated with loneliness.

General Discussion

The aim of this research cycle was to empirically test whether perceived social isolation is associated with heightened bottom-up responses to social threat—reflected in attentional vigilance (RQ1) and affective reactivity (RQ3)—and with reduced top-down regulation of threat-related processing, reflected in inhibitory control (RQ2) and emotion regulation (RQ4). In addition, the research examined the pathways linking early-stage processing and regulatory mechanisms to social cognitive bias (RQ5) and social cognitive capacity (RQ6) in loneliness. The overall pattern of findings supports three key conclusions regarding information processing in loneliness.

First, the results do not support the notion that loneliness is associated with generalized hypervigilance or increased affective responses to socially threatening stimuli. Despite employing a wide range of complementary measures—including explicit behavioral indices (reaction times), neural markers of attentional orienting (N2pc), and latent decision processes captured through computational modeling—Study 1 provided no evidence for heightened vigilance to social threat among lonely individuals at any level of analysis. In Study 2, no evidence for elevated neural markers of early perceptual (P1, N1) or late-stage processing (LPP) was found, providing no support for heightened attentional vigilance or sustained emotional engagement with negative social stimuli among lonely individuals. Likewise, physiological measures (skin conductance) and self-reported affective responses revealed no indication of increased emotional reactivity—in fact, lonely participants reported lower subjective arousal to negative images. The only supported hypothesis was an enhanced P300 amplitude observed in lonely individuals during passive viewing of negative social stimuli. In the context of consistently null effects across other indices, this isolated P300 enhancement is probably best interpreted

as reflecting a specific alteration in evaluative engagement rather than increased bottom-up affective response. In Study 3, loneliness was not associated with increased sensitivity to social cues, such as the ability to recognize emotions or detect social signals. However, loneliness was linked to alterations in early-stage processing of social stimuli, reflected in shorter nondecision times. This facilitated early-stage processing could initially suggest some form of heightened vigilance. Interestingly, the cognitive model of loneliness (Cacioppo et al. 2014) proposes that such increased vigilance should subsequently promote biased interpretations of social stimuli. Yet, our results showed an opposite pattern: when socially threatening stimuli were present, higher social cognitive bias was associated with prolonged, rather than shortened, early-stage processing. Thus, although loneliness itself was related to faster initial engagement with social stimuli, the presence of interpretive biases when the threat stimuli were actually presented appeared to slow down these initial processing benefits in lonely individuals. This suggests that loneliness may involve a specific alteration in early-stage processing, but this alteration does not appear to drive or facilitate the development of negatively biased interpretations at later stages, as proposed by cognitive models of loneliness. Taken together, the findings presented in this thesis suggest that the commonly reported associations between loneliness and negative affective experiences in social situations (Blandl and Eisenberger 2025) do not originate from heightened bottom-up responsivity to social threat, but rather point to the involvement of processes operating at later stages of social information processing.

The second main conclusion emerging from this thesis is that loneliness is primarily associated with biased social information processing, particularly in domains related to interpretation, evaluation, and self-referential judgment, rather than objective decreases in complex abilities associated with cognitive control, emotion regulation or mental state inference. In line with H2, we expected to find an association between loneliness and diminished inhibitory control. Study 1 showed that lower drift rates in lonely individuals could be interpreted as reflecting less efficient maintenance of task-relevant information in the presence of distractors, potentially implicating compromised inhibitory control. However, in Study 2, no relationship was observed between loneliness and performance on a set-shifting task, a behavioral measure of inhibitory control. Furthermore, the results of the Study 3, which has utilized a more complex approach towards modelling of the effects linking drift rate with loneliness while concurrently accounting for the effects of social cognitive capacity, social cognitive bias and objective social isolation has shown no association between drift rates observed during the task and loneliness levels in a large group of participants. Similarly, even though more lonely participants showed decreased impact of cognitive reappraisal use on arousal ratings of the stimuli and declared less frequent use of adaptive strategies in their daily life across self-report measures in Study 2, they did not exhibit decreased ability to utilize cognitive reappraisal to downregulate their physiological response to affective

stimuli, as indicated by ERP and skin conductance findings. The divergence between objective and subjective indices is consistent with the distinction between emotion regulation ability and emotion regulation tendencies or habits, frequently emphasized in the literature (Andrews et al. 2023; Oriyama et al. 2025). Our findings suggest that although lonely individuals are capable of regulating emotions when prompted, they habitually rely on less adaptive strategies and perceive themselves as less effective emotion regulators. A similar dissociation emerged in Study 3 with respect to social cognition. While more lonely individuals did not display reduced social cognitive capacity, whether in processing social cues or attributing mental states, a robust association between loneliness and biased processing of social information was observed. Previous studies have shown that loneliness is consistently linked to lower self-assessed social abilities and reduced perceived social competence (Heinrich and Gullone 2006; Lodder et al. 2016; Sharp et al. 2016; Tsai and Reis 2009), yet the present findings suggest that such negative self-evaluations do not correspond to actual impairments in social cognitive capacity. Taken together, the findings from all studies in this thesis indicate that loneliness is not primarily characterized by deficits in social cognitive or regulatory capacity, but rather by negatively biased interpretation of social information and negative evaluation of one's own social abilities, which may serve as key mechanisms for maintaining the experience of loneliness over time.

The third, more tentative conclusion emerging from the research cycle is that loneliness may be linked to reduced introspective accuracy, the ability to assess one's own mental and emotional states. In Study 2, lonely participants reported blunted arousal responses to negative versus neutral social images during passive viewing and showed less reduction in arousal ratings during cognitive reappraisal. However, this subjective pattern was not reflected in neural measures, as no corresponding effects were observed in Late Positive Potential amplitudes, which are typically associated with emotional arousal. While none of the studies presented in this thesis were specifically designed to study introspective awareness, several lines of indirect evidence from previous research lend support to this possibility. Loneliness has been linked to elevated levels of alexithymia—a trait marked by difficulties identifying and describing internal emotional states, which may reflect broader deficits in introspective access (Qualter et al. 2009; Conti et al. 2023; Zhang et al. 2023). Supporting this, Lodder et al. (2016) showed that adolescents who exhibited greater discrepancies, regardless of direction, between their self-evaluations and peer assessments of social competence were more likely to report loneliness, suggesting that loneliness may reflect inaccurate self-perceptions. Relatedly, Durlak and Tsakiris (2015) found that even brief social exclusion, a state conceptually related to loneliness, disrupted introspective access to internal bodily signals, as measured by a heartbeat perception task. Finally, neuroimaging data from Golde et al. (2019) revealed that lonelier adolescents exhibited reduced activation in the ventromedial prefrontal cortex—a region broadly implicated in subjective valuation of self-relevant and

social information—when evaluating themselves, but not when judging others. While necessarily speculative due to the limitations of reverse inference, this neural pattern may reflect reduced introspective accuracy. Accurately evaluating internal emotional signals is crucial for effective social functioning, as it allows individuals to monitor their own emotional states, adjust their behavior in social interactions, and form realistic appraisals of social situations; difficulties in introspective accuracy may therefore constitute an additional cognitive mechanism contributing to the maintenance of loneliness.

Conclusion

The notion that loneliness is broadly characterized by heightened vigilance to social threat has become central in theoretical models since it was first introduced by Cacioppo and colleagues as part of the Evolutionary Theory of Loneliness (Cacioppo and Hawkley 2009). This perspective has subsequently been reproduced across both academic and popular science literature (e.g., Hertz 2020; Murthy 2020), and at some point has been accepted as a core feature of loneliness. However, the empirical foundation for this view is both limited and indirect. Because the association between loneliness and social information processing was not extensively studied in the past, Cacioppo and coauthors often relied on indirect evidence. E.g., Yamada and Decety (2009) have found that individuals scoring higher on the Fantasy subscale of the Interpersonal Reactivity Index show increased sensitivity to painful facial expressions. They also noted that “According to Davis’s original study [7], the fantasy scale was associated with shyness, loneliness, and social anxiety.” (p.75), thus they conclude that similar effects may possibly be found in individuals with higher dispositional levels in shyness, loneliness, and social anxiety. At the same time, Cacioppo and coauthors cite these results as support for the notion of the increased sensitiveness to the presence of pain in dislikable faces in lonely compared to nonlonely individuals in at least 11 different reviews and theoretical conceptualizations (e.g., Cacioppo et al. 2015; Cacioppo et al. 2014; Cacioppo et al. 2011; Cacioppo and Hawkley 2009). Another example is provided by resting-state connectivity studies, which heavily rely on reverse inference. For example, Layden et al. (2017) reported increased intrinsic connectivity in the right central operculum and right supramarginal gyrus in individuals with higher loneliness scores. Although interpreted as reflecting tonic alertness, these regions serve diverse, likely more fundamental functions, and the study could not determine the specific processes involved, rendering this interpretation largely speculative. In contrast, findings presented in this thesis — obtained using tasks specifically designed to measure bottom-up processes — do not support the idea that loneliness is associated with a broadly heightened bottom-up response to social threat. Instead, the present work proposes a shift in theoretical focus from hypervigilance to social threats toward interpretive and self-referential mechanisms as central features of the psychological profile of loneliness.

Limitations and Further Directions

The empirical work included in this dissertation is entirely cross-sectional, which limits conclusions about the temporal dynamics through which chronic loneliness may affect cognition. Although short-term studies report high test–retest reliability of the UCLA Loneliness Scale (Maes et al. 2022), Mund et al. (2020) found that one-year stability of loneliness is lowest in young adulthood, the life stage examined here. While based on only two longitudinal cohorts, this estimate plausibly reflects the volatility of this period, marked by transitions such as relocation, relationship formation, and entry into the labor market, all of which may recalibrate perceived social connectedness. Because some cognitive and neurophysiological effects may arise only after sustained social disconnection, the cross-sectional design cannot establish whether the observed differences reflect long-term consequences of chronic loneliness or short-term fluctuations. Furthermore, including both transiently and chronically lonely individuals may dilute effects specific to prolonged loneliness, making them harder to detect. Future research should therefore employ multi-wave longitudinal designs spanning at least 6–12 months to distinguish the cognitive and neurophysiological impact of transient and persistent loneliness.

An additional limitation of the present research program lies in the application of a broad set of tasks designed to assess multiple aspects of social information processing. On the one hand, this multi-method approach allows for a more comprehensive investigation of different cognitive mechanisms potentially implicated in loneliness. On the other hand, the diversity of tasks, each employing different designs and targeting distinct cognitive processes, limited the opportunity to investigate any single mechanism in greater depth, as could have been achieved, for example, by systematically modifying parameters within a single paradigm. Moreover, except of the dot-probe task, most tasks were administered only once throughout the project, limiting the possibility to assess the replicability of specific effects across different samples. Finally, the generalizability of the present findings is limited by both the sample characteristics and the experimental paradigms employed. As the studies focused exclusively on young adults, it remains unclear whether similar cognitive and neurophysiological patterns would be observed in other age groups, such as adolescents or older adults, who may experience loneliness in different social and developmental contexts. Moreover, the experimental tasks used in this research, while well-established in cognitive neuroscience, have limited ecological validity and may not fully capture how social information processing unfolds in real-life social situations. Future studies may address these limitations by combining experience sampling methods with ambulatory physiological measurements, allowing for the assessment of cognitive-affective dynamics in naturalistic settings. Additionally, employing dyadic or interactive paradigms could provide further insight into how the cognitive mechanisms identified here operate during actual social encounters.

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ORIGINAL ARTICLE

Can we dissociate hypervigilance to social threats from altered perceptual decision-making processes in lonely individuals? An exploration with Drift Diffusion Modeling and event-related potentials

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Abstract

It has been hypothesized that lonely individuals demonstrate hypervigilance toward social threats. However, recent studies have raised doubts about the reliability of tasks commonly used to measure attentional biases toward threats. Two alternative approaches have been suggested to overcome the limitations of traditional analysis of attentional bias. First, the neurophysiological indicators of orienting to threats were shown to have superior psychometric characteristics compared to overt measures of behavioral performance. The second approach involves utilizing computational modeling to isolate latent components corresponding to specific cognitive mechanisms from observable data. To test the usefulness of these approaches in loneliness research, we analyzed behavioral and electroencephalographic (EEG) data from 26 lonely and 26 non-lonely participants who performed a dot-probe task using a computational modeling approach. We applied the Drift Diffusion Model (DDM) and extracted N2pc—an event-related potential that serves as an indicator of spatial attention. No evidence for social threat hypervigilance has been found in DDM parameters nor in N2pc characteristics in the current study. However, we did observe decreased drift rate and increased variability in drift rate between trials within the lonely group, indicating reduced efficiency in perceptual decision-making among lonely individuals. These effects were not detected using standard behavioral measures used in the dot-probe paradigm. Given that DDM indicators were sensitive to differences in perceptual discrimination between the two groups, even when no overt differences were found in standard behavioral measures, it may be postulated that computational approaches offer a more comprehensive understanding of cognitive processes.

KEYWORDS

affective neuroscience, attentional bias, computational modeling, dot probe, loneliness, perceptual decision making

1 | INTRODUCTION

Perceived Social Isolation (PSI), or loneliness, is a subjective distressing feeling of mismatch between actual and desired social relationships (Cacioppo & Hawkley, 2009). PSI can be caused by objective social isolation but is also present in people with extensive social networks (Coyle & Dugan, 2012). Loneliness is currently perceived as a significant risk factor both for mental and physical health (Matthews et al., 2019); thus, it is increasingly perceived as a public health issue. The negative impacts of loneliness may be particularly striking in the COVID-19 era when social distancing policies increased the risk of PSI (Killgore et al., 2020). To explain the effect of loneliness on an individual's functioning, the Evolutionary Theory of Loneliness (ETL) was proposed (Cacioppo et al., 2014). ETL operationalizes PSI as a warning signal from the body informing about insufficient social bonds, and, as such, it may serve as motivation to reconnect with others. To facilitate reconnection and avoid missing reconnection cues, lonely individuals may be more vigilant toward social signals. However, as cognitive mechanisms are biased toward self-preservation, this adaptation may make one particularly vigilant toward signals of danger, especially in the social domain. As a result, cognitive mechanisms elicited by PSI, which should facilitate social contacts, may hinder an individual's social functioning, such as via hypervigilance toward social threats (Spithoven et al., 2017). In line with this formulation, lonely individuals have been shown to fixate their gaze on threatening social stimuli more quickly (Bangee et al., 2014; Qualter et al., 2013) and to differentiate negative social stimuli from negative non-social stimuli faster at the neural level compared to non-lonely individuals (Cacioppo et al., 2015, 2016).

However, the evidence for the attentional bias toward social threats in loneliness is far from being consistent (Lodder et al., 2015), and the impact of loneliness on social cognitive processes is still being investigated. For example, we have recently shown that objective, but not perceived, social isolation is linked to lower-level social cue detection in a battery of social-cognitive tasks (Okruszek et al., 2021). Heterogeneity of findings in loneliness research may be attributable to significant discrepancies between paradigms used to study the processing of social cues (Spithoven et al., 2017).

Although the number of studies investigating attentional bias to social threats in lonely individuals is relatively limited, attentional bias and hypervigilance to threats has been extensively investigated in specific neuropsychiatric populations, such as individuals with anxiety disorders (Cisler & Koster, 2010). Certain anxiety disorders have been associated with attentional bias to distinctive types of threatening signals (Pergamin-Hight

et al., 2015). For example, hypervigilance toward social threats has been commonly observed for negative social stimuli among individuals with a social anxiety disorder (Bantini et al., 2016). Furthermore, attentional bias modification treatment can be an effective intervention for reducing anxiety symptoms (Linetzky et al., 2015). Thus, it is important to examine the reliability of methods that are commonly utilized to measure attentional bias, most commonly the dot-probe paradigm (MacLeod et al., 2019).

During the standard dot-probe paradigm, research participants are asked to respond a presented target stimulus (e.g., dot), that is preceded by lateralized cues, which can be either non-salient (e.g., two neutral cues) or differ in salience (e.g., threat-related cue vs. neutral cue). By manipulating the presence and location of the salient cue, processes associated with orienting, engaging, and disengaging attention from the stimulus may be examined (Torrence & Troup, 2018). Traditionally, this is achieved by comparing mean Response Times (RTs) to congruent and incongruent trials. The direction of the observed effect is usually interpreted as facilitation (faster reaction in congruent trials) or avoidance (faster reaction in incongruent trials). Accuracy data are rarely used in analysis due to the ceiling effect in non-clinical groups. Moreover, average RTs as a main outcome of the dot-probe task have been subject to considerable criticism due to poor reliability when measured both with the split-half (Kappenman et al., 2014) and test-retest method (Schmukle, 2005).

Internal consistency is also important to consider when designing measures, and can tell us whether a measure can distinguish participant differences enough for correlational analyses (Clayson et al., 2021). Experimental paradigms can minimize between-subject variance to increase chance of detection of within-subject effect (Hedge et al., 2018). Healthy participants usually perform the dot-probe paradigm with high accuracy and have similar RTs; therefore, between-subjects variance is often relatively low. Yet, prior research has found that low reliability does not preclude use of experimental paradigms for analyses of between-group differences (Hedge et al., 2018).

There is also a general lack of consistency in findings across dot-probe behavioral outcomes (e.g., average RT). Reviews of studies that utilized the dot-probe task to measure emotional attention have found either vigilance toward threats (shorter RTs for threat-congruent locations), threat avoidance (longer RTs for threat-congruent locations) and no effects of emotional attention on dot-probe performance (Bantini et al., 2016; Shechner et al., 2012; van Rooijen et al., 2017). Attentional bias may be a function of stimulus onset asynchrony, resulting in a vigilance effect if stimuli are presented with 100 ms duration but an avoidance effect if stimuli are presented for longer (Cisler & Koster, 2010;

Cooper & Langton, 2006; Koster et al., 2006). While this may explain heterogeneity of results in the field to some extent, similar incoherent outcomes are observed when comparing studies with the same stimulus onset asynchrony (Roy et al., 2015). This heterogeneity challenges the utility of RT measures, since they may reflect a composition of attentional effects and other effects, such as cognitive control (Dennis-Tiwary et al., 2019).

Two different ways of overcoming the limitations of classical analysis of the attentional bias in the dot-probe task have been proposed. First, neurophysiological indicators of orienting to threats during a dot-probe task show superior psychometric characteristics compared to overt measures of dot-probe task performance (Kappenman et al., 2014). To the best of our knowledge, there are no prior studies investigating attentional bias in lonely participants using event-related potentials (ERPs). Detection of salient stimuli in one of the visual hemifields is reflected by the enhanced amplitude of the N2pc component, which is defined as the difference between the activity observed between 200 ms and 300 ms in the parieto-occipital regions that are contralateral and ipsilateral to the presented salient target (Mazza et al., 2009). A recent review of studies using facial stimuli has concluded that, despite some inconsistencies across the studies, N2pc may be a marker of attentional bias toward fearful and angry facial expressions (Torrence & Troup, 2018). Furthermore, the presence of salient cues during the dot-probe task has been found to impact ERPs observed in response to target stimuli (Zhang et al., 2017). While the P1 and N170 components are also used in attention research, they do not necessarily provide the same level of specificity as the N2pc in terms of attentional selection processes (Gupta et al., 2019; Verleger et al., 2012). The P1 is thought to reflect the initial sensory processing of a visual stimulus, and the N170 is mainly associated with the processing of faces and other complex visual stimuli (Kiss et al., 2008). Thus, the N2pc appears to be the most suitable measure to study attentional bias.

A second approach that has been proposed to improve reliability of outcome measures of the dot-probe task is to apply computational modeling to disentangle specific processes reflected in reaction time and accuracy data (Takano et al., 2021). Computational models are becoming increasingly popular in the field of neuroscience because of their ability to uncover unobserved parameters of decision making and perceptual processes, which may provide necessary links between overt behavior and neurophysiological processes (Palmeri et al., 2017). Recently, a computational modeling method known as the Drift Diffusion Model (DDM) has been proposed for dot-probe data analyses (Price et al., 2019). Particularly, by modeling RT distributions and accuracies, DDM extracts parameters that

are used to produce optimal fit for one's observed behavior under the assumption that decisions are made by continuously accumulating evidence (information) in noisy environments. Evidence is sampled from the environment until the decision threshold is reached and a response is initiated (Ratcliff & McKoon, 2008). Importantly, DDM allows disentangling various aspects of the decision-making process by extracting parameters with clear psychological interpretation. First, the decision-making process is described by a drift rate (v) parameter; that is, the mean rate of accumulation of information that is needed to reach the response threshold (a), which reflects speed-accuracy tradeoff. However, DDM also accounts for the processes (e.g., perceptual processing, motor response) that are conveyed via non-decision time (t_0) parameter. By separating decision and non-decision making processes, DDM allows for effective measurement of attentional bias observed during the dot-probe task. The aforementioned study by Price and colleagues has found good psychometric characteristics of t_0 parameters and demonstrated negative associations between attentional and emotion control networks and t_0 parameters in fMRI analysis, thus providing a strong rationale for modeling dot-probe data using DDM (Price et al., 2019). Recent collaborative studies have assessed the validity of model-based analysis of RT data, in which seventeen research teams analyzed the same data set using cognitive models (Dutilh et al., 2019). The authors concluded that high agreeableness in conclusions were observed, despite each team using a different modeling approach; this justifies computational-based modeling. However, researcher degrees of freedom had a tangible impact on the results; therefore, parsimonious models are required.

Taken together, evidence suggests that both neurophysiological indicators and computational approaches are reliable ways of investigating the effects of attentional bias observed during the dot-probe paradigm. Given the inconsistencies of the previous literature on the hypervigilance to social threats in loneliness, the current study aims to investigate the presence of attentional bias to social threats in lonely individuals. In the first step, we will analyze the impact of affective stimuli (neutral vs. angry) and task instruction (inhibitory vs. non-inhibitory target location) on explicit behavioral measures (RT), implicit behavioral measures (DDM parameters) and implicit neurophysiological measures (ERP markers). Next, to test predicted by the ELT hypervigilance to social threats in lonely individuals, we will analyze patterns of within-subject results in each group. We hypothesize (1) increased N2pc and (2) shorter non-decision time, in responses to angry faces among lonely individuals compared to their non-lonely counterparts. Furthermore, as increased attentional bias may affect decision-making processes, this study will

include exploratory analyses to examine the influence of loneliness on other DDM parameters.

2 | MATERIALS AND METHODS

2.1 | Participants

For this study, 52 right-handed individuals (32 female) aged 18–35 with no known history of substance abuse, cardiovascular, neurological, or psychological disorders were recruited via social media platforms. Due to the electrocardiographic measurement conducted in the wider study (but not discussed in this article), individuals with a body mass index above 30 were not eligible to take part in the study. Individuals who met the criteria of a depressive episode as measured by the 20-item Center for Epidemiological Studies Depression Scale – Revised (CESD-R) were also not eligible to take part in the study.

Individuals were screened on subjective loneliness, measured by the Polish version of the Revised UCLA Loneliness Scale (R-UCLA; Kwiatkowska et al., 2017). Prior research on the distribution of R-UCLA scores among an independent sample of 1159 young adults aged 18–35 years was used to determine the quartiles of the R-UCLA scores in the Polish population. In the current study, only individuals with R-UCLA scores corresponding with the first (R-UCLA ≤ 32) and fourth (R-UCLA ≥ 49) quartile of all R-UCLA scores were included to create two equi-numerous groups: low-loneliness (Q1) or high-loneliness group (Q4). Both groups were matched in terms of sex ($X^2(1) = 0.73$, $p = .39$) and age (low-loneliness $M = 26.65$, $SE = 1$; high-loneliness $M = 25.92$, $SE = .84$; $t(50) = -0.56$, $p = .58$). Table 1 shows demographic statistics for each group.

2.2 | Stimuli

Stimuli for the current study were selected from the FACES database (Ebner et al., 2010). Overall, 240 faces displaying neutral or angry expressions were selected from pictures of young and middle-aged actors and cropped

into oval-shaped masks sized 522×404 pixels. An equal number of male and female faces were included. The full list of the stimuli used is available in the osf.io repository (osf.io/nkf5c/). All stimuli were adjusted in terms of luminance (mean pixel value of the greyscaled pictorial stimuli – mean luminance = 133.3) and contrast (standard deviation of all pixels – mean contrast = 20.2) using “rgb2gray” function in Matlab.

2.3 | The dot-probe task

The task procedure was programmed using Presentation 21.1. All stimuli were presented on a gray background. Each trial began with a 500 ms display of a fixation cross, followed by the simultaneous 200 ms display of two faces (angry and neutral) on opposite sides of a 24 inch screen (Iiyama prolite PL2483h, refresh rate = 60 Hz) centered at 8.1 degree visual angle from the fixation cross. One third of the trials presented the angry face on the left side, 1/3 on the right, and 1/3 featured two neutral faces. The same actor was presented in each pair of pictures, so in the neutral trials, the same photo was displayed on both sides, while in the angry-neutral trials, the same actor was presented with two different expressions. The trials were counterbalanced with respect to the sex of the actors. Each actor was presented three times over the runs of the task (neutral-neutral, angry-neutral, neutral-angry). The order of the trials was pseudo-randomized, and each trial concluded with the 1000 ms display of a target stimulus (either a horizontal or vertical colon) on either the left or right side of the screen. Each run lasted 7 min and included 240 trials, with one minute of rest in between. In total, the experiment was composed of 3 runs with 720 trials. Task design is shown in Figure 1. Before

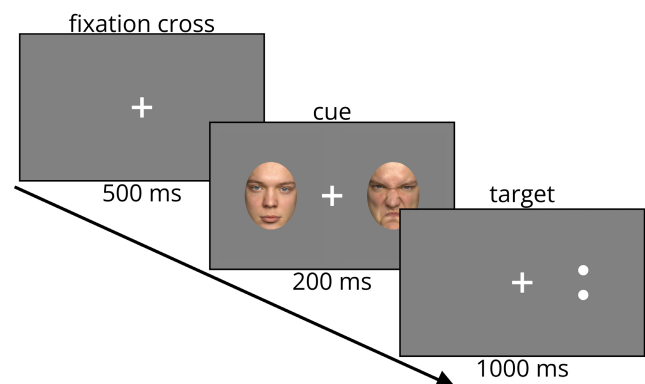


FIGURE 1 Task scheme. In each trial, participants were presented with a fixation cross for 500 milliseconds, followed by a pair of two faces presented for 200 milliseconds. The trial ended with the presentation of the target stimuli for 1000 milliseconds.

TABLE 1 Demographic statistics for each group.

Group	Lonely	Non-lonely
UCLA-R mean score	56.8 ± 4.21	27.7 ± 3.7
% of male	31 ± 47	44 ± 51
Years of education	13.9 ± 2.2	14.8 ± 2.6
Age (years)	25.9 ± 4.3	26.7 ± 5.2

the main task, each participant underwent training. In the first 12 trials, they were asked to respond to the target without preceding faces. For the second part of training (24 trials), both the faces and the targets were included. Due to the programming error at the early stages of experiment design, jitter was not included. Unfortunately, this was not recognized until data collection had already begun. Script used for generating this task in Presentation software may be found online in [osf.io](https://osf.io/nkf5c/) repository (osf.io/nkf5c/).

The experiment was designed in 3×2 manner: Probe Congruence (3 levels): (a) probe congruent – probe occurring in place previously occupied by angry face; (b) probe incongruent; (c) baseline – two neutral faces), target type (2 levels): (a) non-inhibitory – side of colon consistent with an arrow that participant has to press; (b) inhibitory – side of colon inconsistent with an arrow that participant has to press).

Participants were seated 70 cm from the screen and instructed to respond with a right arrow if the dots were presented in a vertical orientation and react with a left arrow if the dots were displayed in a horizontal orientation.

2.4 | Procedure

The experiment procedure was held at the Laboratory of Neurophysiology and Neuromodulation at the Institute of Psychology, Polish Academy of Sciences in Warsaw. Participants first provided their written informed consent, then the experimenters prepared the cap on the participant's head and explained the task instructions. Participants were instructed to press the right arrow button if the target was a horizontal colon and the left arrow button if the target was a colon rotated by 90 degrees, as quickly and accurately as possible. During the task, the participant was alone in a dimly-lit, sound-attenuated room. The procedure was approved by the Ethical Committee at the Institute of Psychology, Polish Academy of Sciences.

2.5 | Power sample calculation

Due to the robustness of the N2pc effect in dot-probe studies (Liu et al., 2020), we expected a large effect size (Cohen, 1988). Power for the ANOVA was set using an α of 0.05, two-level between subject factor, and Cohen f equal to 0.4, and calculated using “WebPower” R package version 0.6. The calculation indicated that a sample of 26 participants per group was sufficient to meet 80% power. However, given that the interaction effect is typically smaller than

the main effect (Li et al., 2006), our study may be underpowered for modulation by group effect based on these parameters.

2.6 | EEG recording and analysis

The EEG signal was recorded from a 64-channel NeuroScan QuikCap connected to a SynAmps RT amplifier. Electrodes on the cap were placed according to the 10/20 international system, with four additional electrodes for electrooculogram monitoring (one above and one below the left eye and one for each corner of the eye). To record data, the CURRY 8 system was used. An online sampling rate was 1000 Hz, and the impedance at each electrode was kept below 5 kOhms. Preprocessing and analysis of the EEG signal were carried out offline using Matlab R2020b toolboxes – EEGLAB 2023.0 (Delorme & Makeig, 2004) and ERPLAB 9.10 (Lopez-Calderon & Luck, 2014). The signal was downsampled to 250 Hz, bandpass filtered with default EEGLAB filter (zero-phase Hamming-windowed finite impulse response filter) with 0.1 and 30 Hz passband edges and -6 dB cutoff frequency, and average re-referenced. Based on visual inspection, signal fragments that were corrupted by noise were removed. Bad channels that exhibited noise were detected with `clean_rawdata` EEGLAB function with autocorrelation criterion set to 0.8 and interpolated with spherical interpolation. Subsequently, the signal was decomposed by the ICA algorithm and then the components representing noise were rejected with use of the ADJUST (Mognon et al., 2011) and MARA (Winkler et al., 2011) algorithms.

To analyze the N2pc, the signal was divided into 700 ms epochs with a 200 ms baseline at the probe onset. Epochs were excluded from further analysis if peak-to-peak amplitude of moving window of size 200 ms and step 20 ms within trial exceeded $\pm 100 \mu\text{V}$ on any of the channels or if the participants provided an incorrect response to the target (overall, 7.1% of data was rejected). Preprocessing script is available in the [osf.io](https://osf.io/nkf5c/) repository (osf.io/nkf5c/). As evidenced by the review of the studies included in the recent meta-analysis of the N2pc response to facial stimuli (Liu et al., 2020), this effect is usually measured over P7 and P8 electrodes and quantified in the time window starting no earlier than 160 and no later than 350 ms post stimulus onset. Thus, upon visual inspection of the current data (Figure 2), we have decided to use signal observed at P7/P8 electrodes within a time window between 250 and 325 ms to quantify N2pc effects. Amplitudes and fractional area latencies were averaged across three conditions: contralateral, ipsilateral, and baseline. In contralateral and ipsilateral conditions, the amplitudes were categorized based on the position of the angry face relative to the

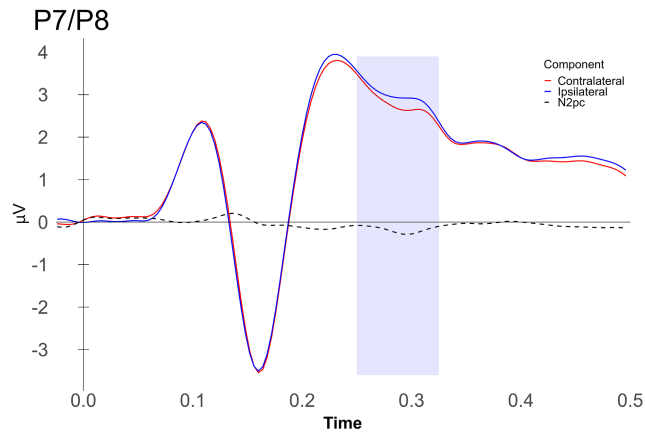


FIGURE 2 Mean N2pc wave averaged on P7 and P8 electrodes.

electrodes. Specifically, in the contralateral condition, the image of an angry face was presented in the visual field opposite to the electrode's position, while in the ipsilateral condition, the image of an angry face was presented in the visual field on the same side of the electrode. Data from both P7 and P8 electrodes were pooled in each condition to obtain measure. The baseline condition served as a reference point for comparison with the Contralateral and Ipsilateral conditions. In the baseline condition, data from trials with two neutral faces were averaged from P7 and P8 electrodes, to establish the magnitude of N2pc when no lateralized threat stimulus is presented. Mean N2pc wave is shown in Figure 2.

2.7 | DDM analysis

Preprocessing of behavioral data and estimation of DDM parameters was conducted in R 4.0.2 programming language (R Core Team, 2013). Trials with no behavioral response or with RTs exceeding two standard deviations from the mean for a given subject under a given condition were excluded from the analysis (4.4% of trials overall). After removing trials, groups of Lonely individuals did not significantly differ in the mean number of trials from Non-Lonely individuals. Participants who had low task accuracy, defined as performance more than two standard deviations from interquartile range, were excluded ($n = 1$, from Non-Lonely group). A final sample of 51 participants (Lonely: $n = 26$, Non-Lonely: $n = 25$) was therefore retained in the analytic sample. Table 2 shows the summary statistics of RTs and accuracy.

We set our model specification allowing the following parameters to be estimated from the data: drift rate (v), non-decision time ($t0$), threshold separation (a), variability of non-decision time ($st0$), and variability in drift rate (sv).

TABLE 2 Summary statistics of response times and accuracy for each group and condition.

Group	Lonely						Non-lonely					
	Congruency			Incongruency			Non-inhibitory			Inhibitory		
	B	C	I	B	C	I	B	C	I	B	C	I
RT M $\pm$ SD	524 $\pm$ 56	525 $\pm$ 61	514 $\pm$ 56	557 $\pm$ 59	559 $\pm$ 58	553 $\pm$ 61	503 $\pm$ 39	509 $\pm$ 41	501 $\pm$ 37	547 $\pm$ 42	552 $\pm$ 44	545 $\pm$ 45
Accuracy (%)	92 $\pm$ 3	93 $\pm$ 3	93 $\pm$ 3	86 $\pm$ 7	86 $\pm$ 7	85 $\pm$ 7	94 $\pm$ 5	94 $\pm$ 5	94 $\pm$ 5	88 $\pm$ 8	88 $\pm$ 8	88 $\pm$ 9
M $\pm$ SD												

Abbreviations: B, baseline; C, congruent; I, incongruent.

We modeled the upper and lower boundaries, respectively, as correct and incorrect responses. “Correctness” modeling may be used instead of choice modeling when both responses share a similar level of difficulty; that is, if the difference in accuracy and RT between the left-side and right-side condition is not important (Voss & Voss, 2007). Therefore, we set the starting point “z” equal to the upper threshold divided by two ($a/2$), indicating no bias toward right and wrong responses.

Point estimates of model parameters have been obtained with the use of differential evolution Markov Chain Monte Carlo (Turner et al., 2013), based on Hawkins et al. (2017). We set prior distribution considerably wide because we had no preceding information about potential shapes of parameters distributions:

$$v \sim TN^{(-5,5)}(0, 2),$$

$$a, sv \sim TN^{(0,5)}(1, 1),$$

$$t0, st0 \sim Beta(1, 1),$$

$TN^{(a,b)}(\mu, \sigma)$ denotes a Truncated Normal distribution with mean μ and standard deviation σ , with a and b as lower and upper limit, respectively. $Beta(\alpha, \beta)$ denotes a Beta distribution with shape parameters α and β .

After the estimation procedure, the convergence of chains was checked with the use of Rubin & Gelman Multivariate Potential Scale Factor (MPSF; Brooks & Gelman, 1998). MPSF for all participants was below 1.15, which indicates that chains did not fail to converge. RTs histogram and DDM generated RTs densities of one participant are visualized in Figure 3.

2.8 | Statistical analysis

2.8.1 | Behavioral measures

All statistical analyses were conducted with R (version 4.0.2) except for the ANOVAs, which were conducted in JASP (version 0.16.1). RTs, drift rate, non-decision time, threshold and variability in drift rate were analyzed using repeated-measures ANOVA with Probe Congruence and Target type as within-subject factors and Group as a between-subjects factor. Holm correction was used for multiple comparison corrections in post hoc testing. The Greenhouse–Geisser correction was applied to the p values when sphericity assumption was violated.

2.8.2 | Erp's components

N2pc component mean amplitude and fractional area latency were analyzed in 3×2 ANOVA with lateralization (3 levels: contralateral, ipsilateral and baseline – both faces neutral) as within-subject factors and Group as a between-subjects factor. Only trials with correct responses were used in analysis. Holm correction was used for multiple comparison corrections in post hoc testing. The Greenhouse–Geisser correction was applied to the p values when sphericity assumption was violated.

2.8.3 | Bayesian analyses

We included additional Bayes factor analyses to quantify the evidence for/against hypotheses, in case the main confirmatory analyses did not produce significant effects (N2pc amplitude/fractional area latency; non-decision

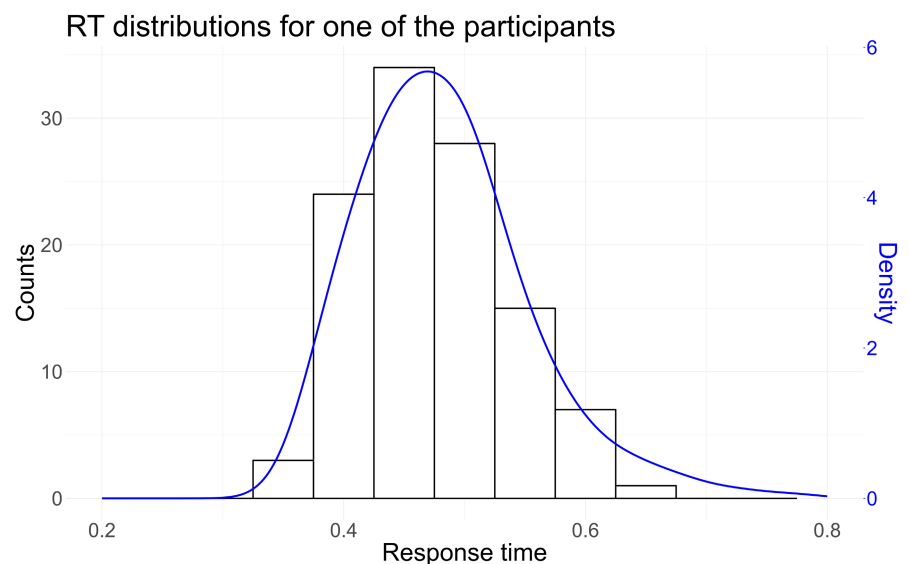


FIGURE 3 Observed RT (histogram) and model generated RT (blue line) for one of the participants in congruent condition, non-inhibitory trials, correct responses. The x axis corresponds to response time in seconds. Left y axis corresponds to counts (histogram), and the right y axis corresponds to the model generated probability density of response time (blue line).

time). Bayes factors were calculated by dividing the likelihood by the prior of the best model, which contains the group term, to the best model that does not contain the group term, as implemented in the Bayesian version of the ANOVA in JASP. Bayes factors were interpreted according to Kass and Raftery (1995).

3 | RESULTS

3.1 | Response times

The main effect of probe congruence was significant ($F(2, 98)=24.34$, $p<.001$, $GGc=0.184$, $\text{partial-}\eta^2=0.33$) with longer RT for congruent trials ($M=0.535$, $SE=0.007$, $95\% \text{ CI } [0.521, 0.549]$) than for baseline ($t(50)=2.7$, $p=.008$, $M=0.532$, $SE=0.007$, $95\% \text{ CI } [0.518, 0.546]$) and incongruent trials ($t(50)=6.93$, $p<.001$, $M=0.527$, $SE=0.007$, $95\% \text{ CI } [0.513, 0.541]$). Significantly longer RTs were found for baseline trials than incongruent trials ($t(50)=-4.05$, $p<.001$). A robust effect was observed for target type ($F(1, 49)=276.23$, $p<.001$, $\text{partial-}\eta^2=0.85$) with longer times compared for Inhibitory trials targets ($M=0.55$, $SE=0.007$, $95\% \text{ CI } [0.536, 0.564]$) compared to

non-inhibitory trials ($t(50)=-16.2$, $p<.001$, $M=0.513$, $SE=0.007$, $95\% \text{ CI } [0.499, 0.527]$). No between-group effect, nor any interaction effects, were found for RTs. Histograms of all participants' single-trial RTs may be seen in Figure 4.

3.2 | N2pc amplitude

In line with previous observations, a significant effect of the lateralization was found ($F(2, 98)=4.8$, $p=.01$, $GGc=0.182$, $\text{partial-}\eta^2=0.089$), with less positive amplitudes observed for contralateral ($M=2.93$, $SE=0.349$, $95\% \text{ CI } [2.233, 3.635]$) compared to baseline ($t(50)=-2.45$, $p=.032$, $M=3.076$, $SE=0.349$, $95\% \text{ CI } [2.375, 3.777]$) and ipsilateral ($t(50)=-2.87$, $p=.015$, $M=3.1$, $SE=0.349$, $95\% \text{ CI } [2.399, 3.801]$) presentation of the angry face, thus implying a classical N2pc effect. The effects of Group ($F(1, 49)=2.27$, $p=.138$, $\text{partial-}\eta^2=0.44$) and Lateralisation $\times$ Group interaction ($F(2, 98)=0.157$, $p=.86$, $\text{partial-}\eta^2=0.03$) were not significant. The Bayes factor for model containing group effect ($BF=0.35$) indicated indecisive strength of evidence for or against presence of group effect.

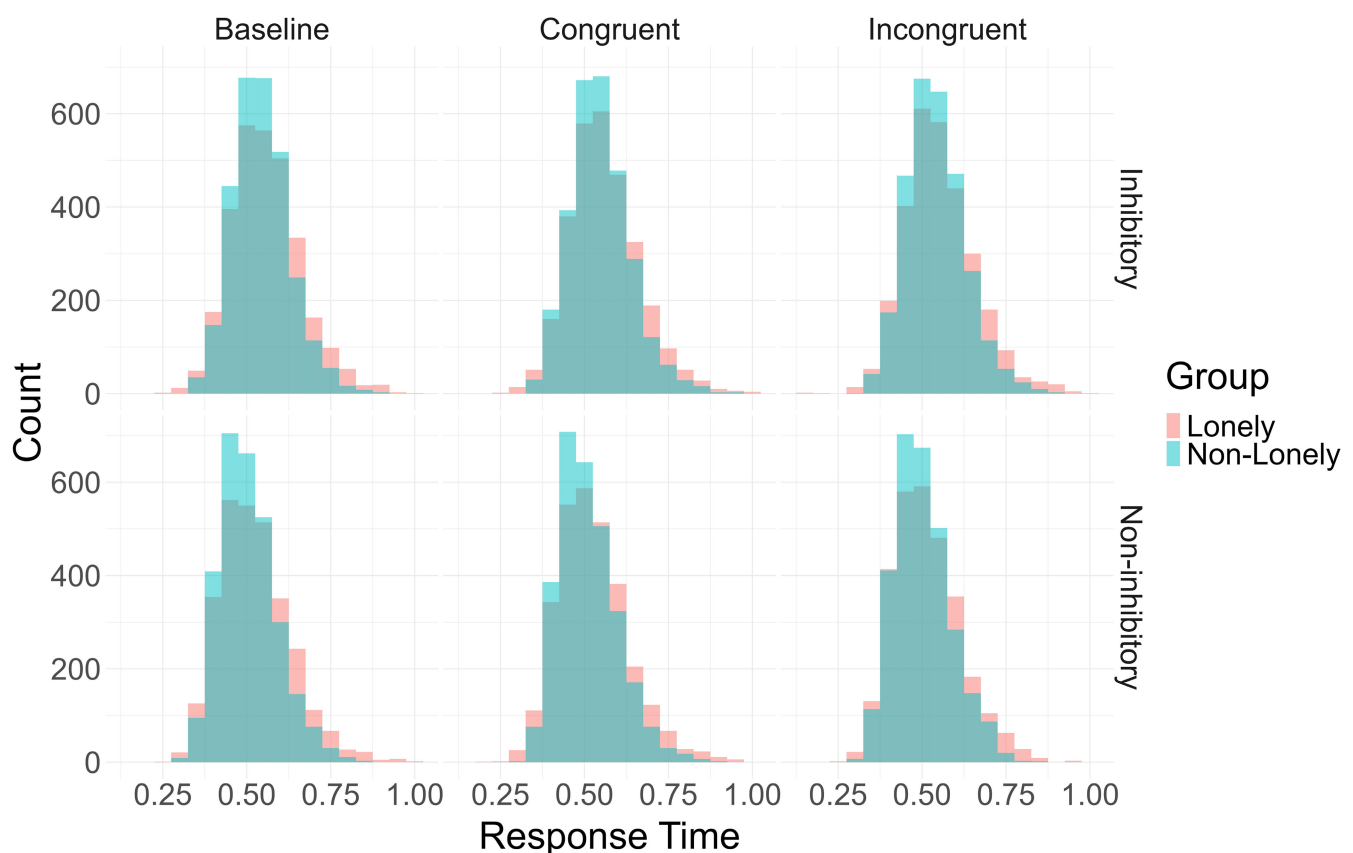


FIGURE 4 Response time histograms for each combination of experimental conditions and group. In columns Probe Congruence conditions, in rows Inhibitory conditions. Groups are overlaid at each plot.

3.3 | N2pc fractional area latency

The effects of Lateralisation ($F(2, 98)=1.094$, $p=.339$, $GGc=0.047$, $\text{partial-}\eta^2\text{-sq}=0.02$) and Group ($F(1, 49)=0.014$, $p=.908$, $\text{partial-}\eta^2\text{-sq}<0.001$) were not significant. The Lateralisation $\times$ Group interaction was also not significant ($F(2, 98)=0.824$, $p=.442$, $GGc=0.047$, $\text{partial-}\eta^2\text{-sq}=0.017$). The Bayes factor for the model containing group effect ($BF=0.47$) indicated indecisive strength of evidence for or against presence of group effect.

3.4 | Non-decision time (t_0)

A significant main effect of Target was observed ($F(1, 49)=252.83$, $p<.001$, $\text{partial-}\eta^2\text{-sq}=0.84$) with shorter t_0 for non-inhibitory ($M=0.318$, $SE=0.006$, 95% CI [0.307, 0.329]) compared to inhibitory targets ($t(50)=-15.9$, $p<.001$, $M=0.356$, $SE=0.006$, 95% CI [0.345, 0.367]). No between group differences ($F(1, 49)=0.049$, $p=.826$, $\text{partial-}\eta^2\text{-sq}<0.001$) or any higher order interactions were found for t_0 . The Bayes factor for the model containing group effect ($BF=0.4$) indicated indecisive strength of evidence for or against presence of group effect.

3.5 | Drift (ν)

A significant main effect of Target was observed ($F(1, 49)=70.84$, $p<.001$, $\text{partial-}\eta^2\text{-sq}=0.59$) with lower drift rate for inhibitory trials ($M=3.65$, $SE=0.09$, 95% CI [3.458, 3.81]) compared to non-inhibitory trials ($t(50)=-8.34$, $p<.001$, $M=4.33$, $SE=0.09$, 95% CI [4.154, 4.507]). A main effect of Group was also found ($F(1, 49)=6.16$, $p=.017$, $\text{partial-}\eta^2\text{-sq}=0.11$) with lower drift rate observed in Lonely individuals ($M=3.8$, $SE=0.11$, 95% CI [3.567, 4.01]) compared to Non-Lonely individuals ($t(49)=-2.48$, $p=.017$, $M=4.18$, $SE=0.11$, 95% CI [3.954, 4.398]). No other effects or interactions were found.

3.6 | Drift variability (sv)

A significant main effect of the probe congruence was observed ($F(2, 98)=4.5$, $p=.013$, $GGc=0.154$, $\text{partial-}\eta^2\text{-sq}=0.084$) with smaller variability in drift rate for congruent trials ($M=0.588$, $SE=0.019$, 95% CI [0.553, 0.623]) compared to baseline trials ($t(50)=-3$, $p=.01$, $M=0.636$, $SE=0.018$, 95% CI [0.6, 0.671]). No significant differences were observed between incongruent trials and other conditions. A main effect of Group was also found ($F(1, 49)=7.382$, $p=.009$, $\text{partial-}\eta^2\text{-sq}=0.131$) with larger sv in Lonely individuals ($M=0.652$, $SE=0.02$, 95% CI [0.609, 0.694])

compared to Non-Lonely individuals ($t(49)=2.72$, $p=.009$, $M=0.57$, $SE=0.02$, 95% CI [0.526, 0.613]). A significant interaction was also found between Target and Group ($F(1, 49)=6.34$, $p=.015$, $\text{partial-}\eta^2\text{-sq}=0.15$) with significantly smaller sv in non-inhibitory trials in Non-Lonely individuals in comparison to inhibitory trials in Non-Lonely individuals ($t(49)=-2.78$, $p=.03$), non-inhibitory trials in Lonely individuals ($t(49)=-3.66$, $p=.003$) and inhibitory trials in Lonely individuals ($t(49)=-3.63$, $p=.015$). No other effects or interactions were found.

3.7 | Threshold separation

Significant main effects of Group ($F(1, 49)=4.35$, $p=.042$, $\text{partial-}\eta^2\text{-sq}=0.08$) and Target ($F(1, 49)=209.01$, $p<.001$, $\text{partial-}\eta^2\text{-sq}=0.81$) were observed, as well as Group $\times$ Target interaction ($F(1, 49)=5.23$, $p=0.027$, $\text{partial-}\eta^2\text{-sq}=.1$). Within groups, all inhibitory trials had a significantly larger threshold ($p<.001$) than non-inhibitory trials. Lonely individuals had a significantly smaller threshold than Non-Lonely individuals in the non-inhibitory condition ($t(49)=-2.09$, $p=.042$).

4 | DISCUSSION

The aim of the present study was to examine mechanisms associated with social threat hypervigilance in lonely individuals by using a well-established attention cueing paradigm (dot-probe task). By using both neurophysiological indicators of task performance and computational modeling methods, we aimed to separate processes associated with bottom-up orienting to social threats from top-down responses to task demands.

Contrary to our initial hypothesis, we did not observe any evidence of hypervigilance to social threats in lonely individuals in the current study. No differences were found between groups in the N2pc effect observed in response to the presentation of angry and neutral faces (H1). A recent meta-analysis of 13 studies, with 534 participants overall, has found increased N2pc amplitude for affectively valenced facial expressions (Liu et al., 2020). In line with these observations, we have observed the N2pc effect for angry compared to neutral faces presented during the dot-probe task, thus replicating the so-called "anger superiority effect" (Ceccarini & Caudek, 2013; Liu et al., 2020). This effect has been linked to the initial orientation of attention toward social threat cues (Torrence & Troup, 2018). Yet, no evidence for increased orienting toward angry faces was found in lonely individuals compared to non-lonely individuals. Furthermore, no evidence for social threat hypervigilance was found in mean RT and

in the DDM parameters, particularly t_0 (H2); this parameter, which accounts for processes that are not linked to the decision making per se, has been interpreted as a proxy of the processes linked to attentional bias during dot-probe task (Price et al., 2019). Taken together, no increased social threat orienting was observed with behavioral, computational or neurophysiological analyses utilized in the current study. At the same time, it is worth noting that previous electrophysiological studies showed increased early orienting toward negative social cues when compared to negative non-social cues (Cacioppo et al., 2015, 2016). Thus, as only social stimuli were presented as a threat and non-threat stimuli in the current study, the between-group effects may not have been elucidated.

Furthermore, we found a group effect in drift rate, drift rate variability and threshold separation. Lonely individuals accumulate evidence at a lower rate than non-lonely individuals. Drift rate is a parameter that indicates the mean portion of evidence collected per unit of time. Therefore, it is interpreted as the level of discriminability of stimuli in between conditions comparison, and as a measure of perceptual sensitivity in between group comparisons (Voss et al., 2004). Thus, the results of the current study suggest that perceptual sensitivity of lonely individuals is compromised in comparison to non-lonely individuals. However, this difference cannot be observed with only mean RT because such analysis does not take into account the shape of the RT distributions and accuracy data. Moreover, in the current study, lonely individuals presented larger variability in drift rate, which is a measure of noise between trials. The source of this noise may be external (linked to stimuli that vary in perceptual difficulty) or internal (trial-to-trial fluctuation in attention, motivation, or fatigue) (Ratcliff et al., 2018). As all participants were subjected to the same set of stimuli, it could be assumed that this difference comes from internal noise; that is, the decisional process of lonely individuals is less stable between trials. Interestingly, lonely individuals exhibited a lower threshold than non-lonely individuals, but only during non-inhibitory trials in the current study. This finding indicates that lonely participants executed the task faster, but less accurately when the perceptual load was low. However, when perceptual load increases, this difference disappears. A similar effect was also observed in the case of drift rate variability, which may arise from suppressing the impact of potential distractors by adopting a narrow attentional window to account for higher perceptual demands (Biggs & Gibson, 2018). Thus, the impact of threatening stimuli on lonely individuals may interact with the perceptual difficulty of the task. Taken together, the results of the current study suggest that reduced perceptual sensitivity may be found in lonely individuals. These effects were found regardless of the type of

probe, and so may stem from altered processing of social stimuli, which in turn reduces efficiency in cognitive tasks in lonely individuals. According to ELT, social stimuli should produce stronger attentional effects in lonely individuals. Thus, loneliness may decrease efficiency while switching between social perception and task demands in complex tasks.

At the whole sample level, we have observed a pattern suggesting attentional avoidance. Participant responses were significantly slower in trials in which the position of the probe was congruent with the target, which suggests that attention was driven away from threatening stimuli. Importantly, the effect of congruence was not related to the DDM t_0 or v parameters, both of which have previously been shown to be linked to perceptual load (Thompson & Steinbeis, 2021). Previous studies (Weindel et al., 2021) have found that non-decision time is longer when perceptual demands increase, as more time is needed to encode the stimuli. Similarly, higher perceptual demands make evidence sampling more difficult and, therefore, negatively impact drift rate. Lack of observed differences in non-decision time between probe conditions may indicate that longer RTs in congruence conditions are not driven by altered time of perceptual processing of stimuli. Correspondingly, the lack of observed differences between conditions in drift rate implies that each condition is similar in terms of perceptual difficulty. The results reveal that variability in drift rate decreases when a salient cue is present, especially under congruent conditions. On a behavioral level, reduced variability in drift rate in congruent conditions has been found to result in longer, yet more accurate, responses (Ratcliff & Tuerlinckx, 2002), suggesting that the presence of salient stimuli sustains attention on tasks by reducing variability between trials in evidence sampling.

The current study has several limitations. First, the sample size collected was relatively small in order to detect possible modulation effects. A Bayes factor analysis was performed for the hypotheses, which did not produce significant effects, and revealed that no sufficient evidence was gathered in the study to either accept or reject some of the hypotheses of the current study, thus emphasizing that further research in this area should be based on the more numerous samples of participants. Second, there was a lack of non-social stimuli presented during the task. Therefore, it cannot be inferred if the decrease in perceptual sensitivity during decision making in lonely individuals is limited to social stimuli only. The results observed in the current study could be attributed to less expertise in facial recognition in lonely individuals. While we did not measure social cognitive capacity in participants of the current study, our previous research has shown that objective, rather than perceived,

social isolation may predict low-level social cues processing in non-clinical participants (Okruszek et al., 2021). Thus, we have re-examined the results of the current study with the measure of the objective social isolation (the Lubben Social Network Scale) as a covariate and found that inclusion of such covariate does not affect the results reported in the current manuscript. Still, incorporation of the non-social stimuli and objective measures of social isolation could prove beneficial and may be advantageous for future studies in this field, to allow investigation of whether the decrease of perceptual sensitivity is limited to social stimuli or may be a generalized effect in lonely individuals. Third, we did not gather arousal and valence ratings of photos from participants. Previous research has documented abnormal response to both affective and neutral facial vignettes in individuals from clinical populations; for example, Anticevic et al. (2012) has found that some of the differences in neural activity observed in patients with schizophrenia may be accounted for by increased neural response to neutral faces. While the current study investigated loneliness in a non-clinical population of participants, without non-social control stimuli and behavioral ratings of the pictorial stimuli utilized in the study, it may be that more lonely participants perceived neutral facial stimuli in a different way than their non-lonely counterparts. Fourth, the absence of jitter inclusion in our experimental design may have potentially influenced the results. However, upon comparing the average amplitude of the signal in the baseline period between groups, we did not observe any significant differences. Therefore, we believe that the lack of jitter inclusion might not have had a substantial impact on the outcome of our study. Fifth, while the application of a computational approach provided novel insights into the results of the current study, we analyzed neural and behavioral data independently. It may be beneficial to employ joint modeling to further investigate cognitive effects of loneliness by applying a framework that allows modeling link between DDM parameters and neural measures (Turner et al., 2015).

AUTHOR CONTRIBUTIONS

Szymon Mąka: Conceptualization; data curation; formal analysis; investigation; methodology; software; validation; visualization; writing – original draft; writing – review and editing. **Marta Chrustowicz:** Investigation; project administration. **Łukasz Okruszek:** Conceptualization; funding acquisition; resources; supervision; writing – review and editing.

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DATA AVAILABILITY STATEMENT

The raw data can be downloaded from the [openneuro.org](https://openneuro.org/datasets/ds004626) repository (openneuro.org/datasets/ds004626), while additional materials such as code and stimulus list are available on the osf.io repository (osf.io/nkf5c).

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Discrepancy between self-report and neurophysiological markers of socio-affective responses in lonely individuals

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Abstract

Theoretical models suggest that loneliness may be linked to abnormal social information processing and reduced emotion regulation capacity; yet these effects have mostly been investigated using self-report methods. Therefore, the current preregistered study examined whether loneliness is associated with objective and subjective markers of bottom-up emotional reactivity and cognitive reappraisal efficiency in a cohort of 150 young adults (18–35 years old) recruited to reflect the distribution of loneliness scores in the Polish population. Participants completed an emotion processing and regulation task with both social and nonsocial stimuli while their electroencephalography activity was recorded. Contrary to the hypotheses, when faced with socio-affective stimuli, lonelier individuals did not exhibit abnormal markers of early sensory processing, late sustained processing, or decreased efficiency in reappraisal use, as indicated by event-related potential markers. Only a weak

association between loneliness and an increased P300 response to negative vs. neutral social stimuli was found. This pattern of findings did not align with subjective arousal reports, which suggested a decreased response to negative social stimuli and reduced cognitive reappraisal efficiency in lonelier participants. These results suggest that loneliness is linked to disruptions in emotional self-awareness rather than an abnormal response to socio-affective stimuli.

Keywords: cognitive reappraisal, EEG, emotion regulation, hypervigilance, loneliness

Introduction: Understanding the interplay between loneliness and health is among the current public health priorities, as indicated by the recent United States Surgeon General's Advisory on "Our Epidemic of Loneliness and Isolation" (2023). This interest is driven by the increasing prevalence of loneliness across Western populations and its negative mental health effects (J. T. Cacioppo & Cacioppo, 2018; Matthews et al., 2019). Loneliness has been considered a potent social stressor that triggers a cascade of cognitive and physiological responses (Cacioppo & Hawkley, 2009). Current evidence suggests that loneliness is associated with abnormal social information processing, manifesting as heightened sensitivity and increased attention toward social threats (Qualter et al., 2013). This tendency may impede individuals from utilizing their top-down resources in social situations (including emotion regulation or taking others' perspectives). Extensive evidence links loneliness to self-reported emotion regulation difficulties, as highlighted by a recent meta-analysis of 61 self-report studies involving over 40,000 participants, which found that loneliness is associated with a greater reliance on maladaptive emotion regulation strategies, such as rumination and suppression, as well as overall emotion regulation difficulties (Patrichi et al., 2024). The imbalance between bottom-up signaling and top-down cognitive control of emotion is considered one of the main drivers of problems encountered by individuals with serious mental illness (Quidé et al., 2012). Moreover, the omnipresence of situations requiring individuals to override automatic responses to potential threats is

central to many stress theories, given the abundance of potential stressors in modern environments (Brosschot et al., 2018; Quidé et al., 2012; Thayer & Lane, 2000).

Rich and robust methodologies for studying the interplay between emotion and cognition have been developed over the past four decades (Dolcos et al., 2011). Neuroscience studies seem particularly important here, as they have provided valuable insights into the neural architecture of bottom-up salience detection (Vuilleumier, 2005) and top-down emotion regulation (Ochsner & Gross, 2005), as well as the time course of these processes. The latter has helped to disentangle the temporal dynamics of perceptual, attentional, and higher-order processes engaged when bottom-up and top-down processes interact (Dolcos et al., 2011). These studies were mostly conducted using neurophysiological measures and event-related potential (ERP) methodology. Most ERP studies focused on the process of stimulus encoding based on the modulation of specific neurophysiological responses, indexed by increased amplitudes or shorter latencies of early (perceptual) ERP components (positive 1 [P1] and N2-posterior contralateral [N2pc]) (Liu et al., 2020; Smith et al., 2003), and later ERPs, associated with attention toward salient stimuli and memory encoding, such as P300 (Ibanez et al., 2012) or late positive potential (LPP) (Hajcak & Foti, 2020); (Weymar et al., 2009); (Schupp et al., 2000).

Of all electrophysiological markers of emotional modulation, LPP has demonstrated the highest stability and internal consistency. It can also be reliably quantified, even with relatively few trials (Moran et al., 2013). LPP amplitude has been identified as a sensitive marker of attentional bias toward negative social stimuli in healthy individuals with high levels of social anxiety, even in the absence of overt behavioral markers of threat response (Moser et al., 2008). A combined electroencephalography and functional magnetic resonance imaging study found that increased LPP responses to negative social stimuli are accompanied by stronger activation in cortical areas involved in visual and social perception (Michałowski et al., 2017). Importantly, LPP has also been effectively used as a marker of emotion regulation strategies, such as reappraisal, which involves reinterpreting the meaning of an emotional stimulus to alter—primarily reduce—its emotional impact. Successful

reappraisal considerably decreases LPP amplitude when applied during the presentation of negative emotional stimuli (Hajcak et al., 2010; Kennedy & Montreuil, 2020). In addition, compared to other emotion regulation strategies, such as distraction, reappraisal has a longer-lasting effect. Stimuli that have been reappraised elicit a more attenuated LPP upon re-exposure than those initially regulated through distraction (Harrison & Chassy, 2017; Thiruchselvam et al., 2011).

Despite the availability of well-developed methodologies and reliable neurophysiological markers for studying affective responses—such as the LPP—the association between loneliness and the neurophysiological underpinnings of affective stimuli processing remains largely unexamined, and the available findings are inconsistent. For example, electroencephalography (EEG) studies using microstate analysis have suggested that lonely individuals exhibit faster differentiation of negative social stimuli than nonlonely individuals (S. Cacioppo et al., 2015, 2016). However, a study employing the well-established dot-probe task found no neurophysiological evidence of loneliness-related social threat hypervigilance, as indicated by the P1 and N2pc components (Mąka et al., 2023). To the authors' best knowledge, no studies have investigated the association between loneliness and LPP, a robust and widely recognized marker of sustained attention and emotion regulation in response to emotionally evocative stimuli.

Given these gaps, the present study aimed to investigate how loneliness is linked to responses to socio-affective information and emotion regulation by integrating self-report and neurophysiological markers. Specifically, we examined whether chronic loneliness is associated with heightened neural and physiological responses—such as early and late ERP amplitudes and Galvanic Skin Response (GSR)—to negative than to neutral social stimuli. In addition, we explored whether loneliness undermines the effectiveness of cognitive reappraisal as an emotion regulation strategy, as reflected in both subjective evaluations and neurophysiological markers.

Furthermore, the question arises as to whether loneliness is directly linked to the above-mentioned effects, given that it is also associated with factors that may influence

emotion processing and regulation. Both depressive (Etkin & Wager, 2007; Zhang et al., 2022) and social anxiety (Etkin & Wager, 2007; Zhang et al., 2022) symptoms may heighten bottom-up responses to negative stimuli and could act as mediators through which loneliness affects emotional reactivity (J. T. Cacioppo et al., 2006; Lim et al., 2016). Loneliness has also been associated with a lower reported use of adaptive emotion regulation strategies, particularly cognitive reappraisal ($r = -0.23$) (Patrichi et al., 2024), suggesting that lonely individuals tend to engage in reappraisal less frequently in real-life situations. This reduced tendency to use reappraisal may, in turn, contribute to diminished capacity for its effective implementation. In other words, individuals who reappraise less frequently may also struggle to apply it when needed (Silvers & Guassi Moreira, 2019). Another key factor that may mediate the effects of loneliness is cognitive control—the ability to regulate thoughts and behaviors by managing attention, inhibiting impulses, and updating goal-relevant information (Miyake & Friedman, 2012). Cognitive control is crucial for emotion regulation, enabling individuals to reappraise emotional stimuli and shift attention away from distressing content. As mentioned above, the heightened attentional biases toward socio-affective information associated with loneliness require greater compensatory top-down cognitive control (J. T. Cacioppo & Hawkey, 2009). Supporting this, recent meta-analytic evidence indicates that neural networks related to loneliness and cognitive control are functionally connected. Lonely individuals appear to upregulate cognitive control to compensate for their increased attention to socio-affective information; however, this prolonged effort may deplete cognitive resources, ultimately leading to affective dysregulation (Wong et al., 2022). These findings suggest that cognitive control deficits may be a key mechanism linking loneliness to impaired emotion regulation efficiency. Finally, this study examines the roles of depression and social anxiety as potential mediators of the socio-affective response sensitivity observed in lonely individuals. In addition, we assess the contributions of cognitive control and the frequency of cognitive reappraisal use to the success of emotion regulation in lonely individuals.

Materials and Methods

Participants

A total of 150 predominantly right-handed, native Polish speakers aged 18–35 with normal or corrected-to-normal vision were recruited via online advertisements from a nonclinical population. During the initial online screening, participants completed the Polish version of the University of California, Los Angeles Revised Loneliness Scale (UCLA-R) (Kwiatkowska et al., 2017) and were assessed for exclusion criteria. Individuals with neurological or psychiatric disorders, substance abuse, or cardiovascular conditions were excluded. Additional exclusion criteria included (i) dysphoria >11 or anhedonia >7 on the Polish version of the revised Center for Epidemiologic Studies Depression Scale (CESD-R, (Koziara, 2016) and (ii) body mass index >30. To ensure full coverage of the loneliness spectrum, quota sampling was applied, with 15 participants per UCLA-R decile based on data from 2,521 participants from our prior studies (<https://osf.io/qzxay>). The final sample (N = 148; 77 women, mean age = 25.3 ± 4.4 years) was obtained after excluding two participants who did not complete the study. All participants provided written informed consent, and the study procedures were approved by the Ethical Committee at the Institute of Psychology, PAS (decision 16/VI/2021). Participants received 200 Polish Zloty (approximately 45 United States dollars) for study completion. The sample size was determined to detect a correlation one-half a standard deviation below the average effect size in personality research ($r = 0.17$, Mar et al., 2013).

Procedure

The study procedure consisted of two sessions conducted at the Laboratory of Neurophysiology and Neuromodulation at the Institute of Psychology, Polish Academy of

Sciences. During the first session, participants completed a series of behavioral tasks, including the Set-Shifting paradigm reported in this study, as well as a set of social cognitive tasks that were unrelated to the current study. In addition, they performed the Emotion Processing and Regulation Task, during which EEG activity was recorded. Between the two sessions, participants were asked to complete a set of online questionnaires assessing emotion regulation and psychopathology, which are described in detail below.

Emotion processing and regulation task

Before completing the main tasks, participants were informed about how to use cognitive reappraisal strategies and were trained to generate reinterpretations of unpleasant stimuli to reduce their emotional responses (full manual in Polish may be found at <https://osf.io/dsvtg/>). For example, in response to an image depicting a sinking ship, they were encouraged to think, “Although the ship was sinking, all passengers and crew managed to reach the lifeboats safely.” Participants were then asked to generate their reinterpretations of the stimuli in the training set and report them to the experimenter. Once the training was completed and the experimenter determined that the participant was able to successfully reappraise negative stimuli, the main experimental procedure began. If necessary, the instruction and training were repeated. During the Emotion Processing and Regulation Task, participants viewed a total of 240 images while EEG activity was recorded. These images included 80 negative social images, such as riots and violence; 80 negative nonsocial images, such as snakes and injured animals; 40 neutral social images, such as pedestrians; and 40 neutral nonsocial images, such as objects. The images were presented in two runs of 120 pictures each, with a break in between. To ensure consistency, the stimuli were matched for luminance and contrast, with full details provided in the Supplementary Materials. Each trial began with a 1-s cue instructing participants to either WATCH or REAPPRAISE the upcoming stimulus, followed by a 5-s presentation of the image. After viewing the image, participants rated arousal and valence using a 9-point Self-Assessment

Manikin scale. Ratings were given freely, with no time constraints. A fixation cross was presented for 1–2 s as the intertrial interval following each trial. Neutral images were always preceded by WATCH cues, while negative images were equally assigned to either WATCH or REAPPRAISE cues. The experimental design followed a 3 x 2 factorial structure, with Condition (Reappraise Negative, Watch Negative, and Watch Neutral) as one factor and Content (Social, Nonsocial) as the other. The presentation of cues was counterbalanced across participants (full details are provided in the Supplementary Materials). A schematic representation of the task is shown in Figure 1.

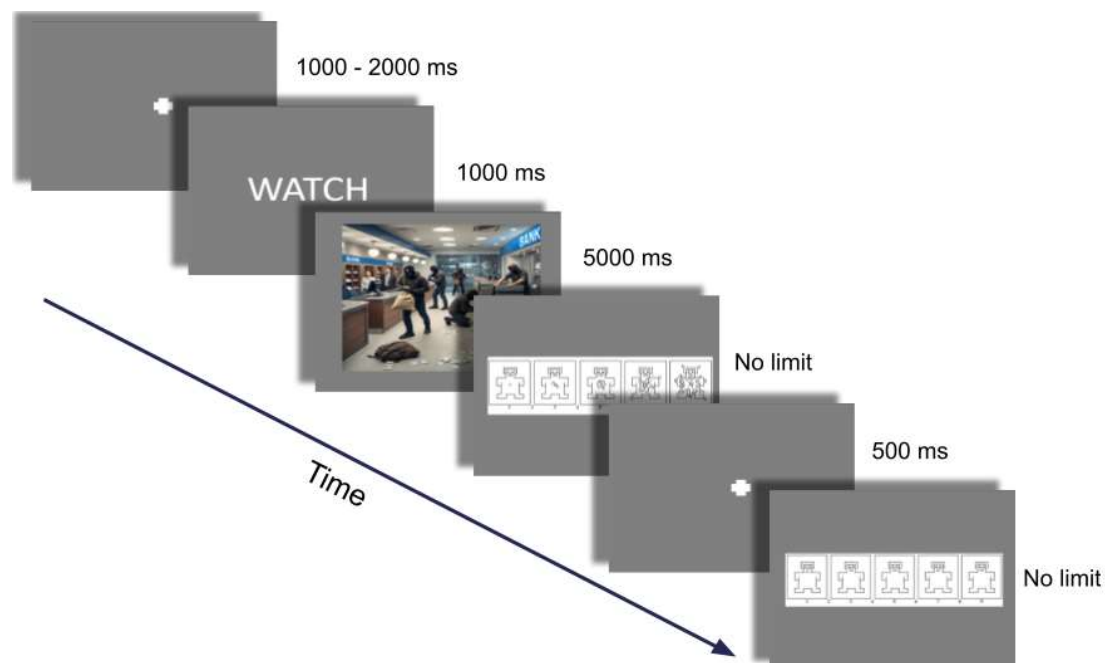


Figure 1. Emotion processing and regulation task trial scheme

Mediator variables

Mediator variables were assessed using both questionnaire and behavioral measures. Depressive symptoms were measured with the CESD-R (Koziara, 2016), while social anxiety was assessed using the Liebowitz Social Anxiety Scale (LSAS) (Liebowitz, 1987). Emotion regulation was evaluated with the Emotion Regulation Questionnaire (ERQ) (Gross

& John, 2012) and the Cognitive Emotion Regulation Questionnaire (CERQ) (Marszał-Wiśniewska & Fajkowska, 2010). However, only the Cognitive Reappraisal subscale from the ERQ and the Principal Component Analysis-derived Cognitive Reappraisal factor from the CERQ were included in the analyses. CERQ Principal Component loadings (Table S2) and summary statistics for the factors (Table S3) are presented in the Supplementary Materials. All scales demonstrated good to excellent reliability in the current sample (Cronbach's $\alpha = 0.72\text{--}0.95$). In addition, cognitive control—specifically set-shifting ability—was behaviorally assessed using the Set-Shifting Task (McRae et al., 2012). Further details on each variable and its assessment can be found in the Supplementary Materials.

EEG recording and processing

EEG data were recorded using a 64-channel QuickCap and a Neuroscan SynampsRT amplifier (1000 Hz sampling rate). In addition, four electrodes were placed to capture electrooculogram signals. Electrodermal activity (EDA) was recorded from the left little and ring fingers using the high-impedance Synamps input. Impedances were maintained below 5 k Ω to ensure quality. Offline processing of EEG data was conducted using Matlab R2020b toolboxes (EEGLAB 2023.0; ERPLAB 9.10). The signal was bandpass filtered (0.1–30 Hz, zero-phase Hamming-windowed FIR filter), downsampled to 250 Hz, and re-referenced to the average mastoids. Noisy channels were detected using clean_rawdata EEGLAB function with autocorrelation criterion set to 0.8 and removed (mean [M] = 1.93, standard deviation [SD] = 1.27, range = [1, 7]). Independent component analysis was performed, and noise components were rejected using the ADJUST algorithm (Mognon et al., 2011). Previously removed channels were interpolated, and the signal was segmented into 5 s epochs with a 200 ms baseline. Trials with residual artifacts ($> \pm 100$ μ V in peak-to-peak amplitude within a 200 ms moving window and 100ms step) were rejected (M = 9.3, SD = 16.2, range = [0, 140]). If more than 50% of trials in any Condition $\times$ Content cell were marked as artifacts, manual artifact rejection was performed to assess whether the data could be salvaged, with

all annotations documented for full reproducibility. If fewer than 50% of trials in any cell remained valid after this process, the participant was excluded from further analysis ($n = 1$). The EEG preprocessing code is available at <https://osf.io/nkf5c/>.

ERP extraction

The scalp amplitude distribution of the grand average waveform is presented in Figure S1 (Supplementary Materials). To analyze the timing and scalp distribution of specific preregistered contrasts, we employed a mass univariate statistical approach (Groppe et al., 2011). EEG signals were averaged for each condition and stimulus type, and four difference waves were computed: (a) Watch Negative – Watch Neutral and (b) Reappraise Negative – Watch Negative, each analyzed separately for social and nonsocial stimuli. T-tests were conducted at each electrode and time point (4–4996 ms), with false discovery rate correction (Benjamini & Hochberg, 1995) applied to control false positives at a nominal alpha level of 0.05. Significant differences in the Watch Negative – Watch Neutral contrast were observed across almost the entire scalp (Figure 2, left column). In contrast, Reappraise Negative – Watch Negative effects were found throughout most of the signal duration on posterior and midline electrodes, with anterior activity between 1–3 s (Figure 2, right column). ERP components P1, negative 1 (N1), early posterior negativity (EPN), P300, and LPP exhibited considerable effects and were selected for further analysis. Based on mass univariate plots and grand average waveforms, P1 (90–140 ms) and N1 (130–190 ms) were defined as instantaneous peaks at Oz, with both peak amplitude and latency extracted. EPN was measured as the mean amplitude (200–300 ms) at Oz. P300 and LPP were extracted from averaged centroparietal electrodes (CP1, CPz, CP2, P1, Pz, P2) and analyzed across four-time windows: P300 (350–500 ms), early LPP (500–1200 ms), middle LPP (1200–2500 ms), and late LPP (2500–5000 ms). Figure 3 illustrates the averaged ERP waveforms.

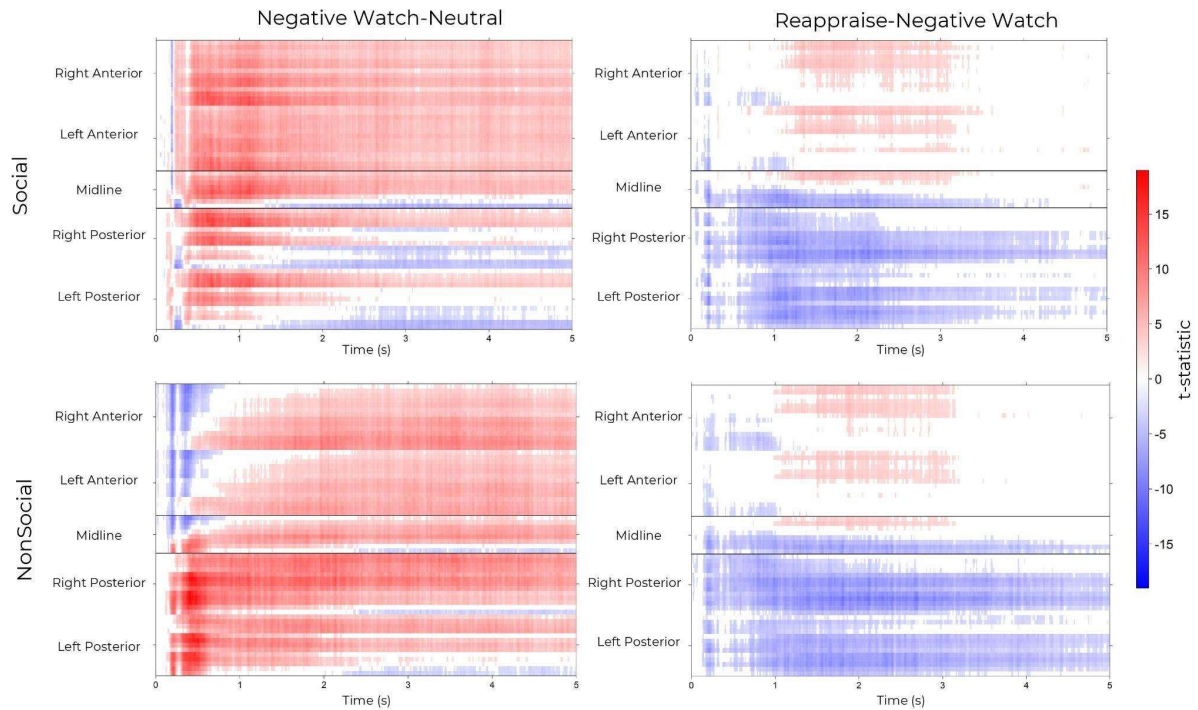


Figure 2. Mass univariate analysis results. The left column shows the Watch Negative - Watch Neutral contrast, while the right column shows the Reappraise Negative - Watch Negative contrast. The top row represents social stimuli, and the bottom row represents nonsocial stimuli. Each panel displays t-statistics over time and scalp regions, with red indicating significant positive t-values, blue indicating significant negative t-values, and white representing non-significant differences (FDR-corrected at $\alpha = 0.05$).

Abbreviation: FDR: False discovery rate

Electrodermal Activity

EDA preprocessing was conducted in Python (3.8.12) using NeuroKit2 (0.1.4.1). The skin conductance signal, measured in microsiemens (μS), was cleaned using a 4th-order Butterworth filter with a 3-Hz cut-off. Visual inspection identified artifacts due to loose electrodes, characterized by sharp drops to near zero. These artifacts were automatically detected and removed. Participants with <50% valid trials in any condition were excluded ($n = 16$). To extract the tonic component, a 2nd-order Butterworth filter with a 0.05-Hz cut-off was applied, following Biopac's Acknowledge approach. The tonic signal was then subtracted to isolate the phasic component. The processed signal was segmented into 6-s epochs with a 1-s pre-stimulus baseline. Event-related GSR was averaged between 2–5 s post-stimulus.

Statistical analysis

Behavioral measures (arousal and valence), EDA, and ERP difference scores were calculated separately for social and nonsocial stimuli. The scores were computed for Watch Negative – Watch Neutral and Reappraise Negative – Watch Negative conditions and used as the primary outcome measures for the task. A paired-sample t-test was conducted to determine whether the means of the measures used to construct these difference scores differed significantly. Next, the difference scores were correlated with UCLA-R loneliness scores. Following our preregistered approach, these primary task outcomes were used in mediation analyses. First, we examined whether the Watch Negative - Watch Neutral difference for social stimuli was linked to UCLA-R scores through psychopathological variables, specifically LSAS and CESD scores. Next, we tested the associations between the outcomes from the Reappraise Negative – Watch Negative condition for social stimuli and UCLA-R scores via Set-Shifting Cost, the Cognitive Reappraisal subscale of the ERQ, and the Cognitive Reappraisal principal component of the CERQ. Before conducting mediation analyses, correlations between the independent variables and mediators were assessed. Mediation analyses were performed using the 'lavaan' R package (version 0.6-16). A Structural Equation Model was used to examine mediation effects, allowing the independent variable to predict both the mediators and dependent variable directly. Mediation effects were evaluated by testing the statistical significance of the indirect effect, calculated as the product of the path coefficients linking the independent variable to the mediator and the mediator to the dependent variable. To minimize the number of models tested, mediation analyses were conducted only when loneliness showed a significant relationship with the dependent variable. Code used to fit models is available at (<https://osf.io/nkf5c/>).

Results

Centro-parietal

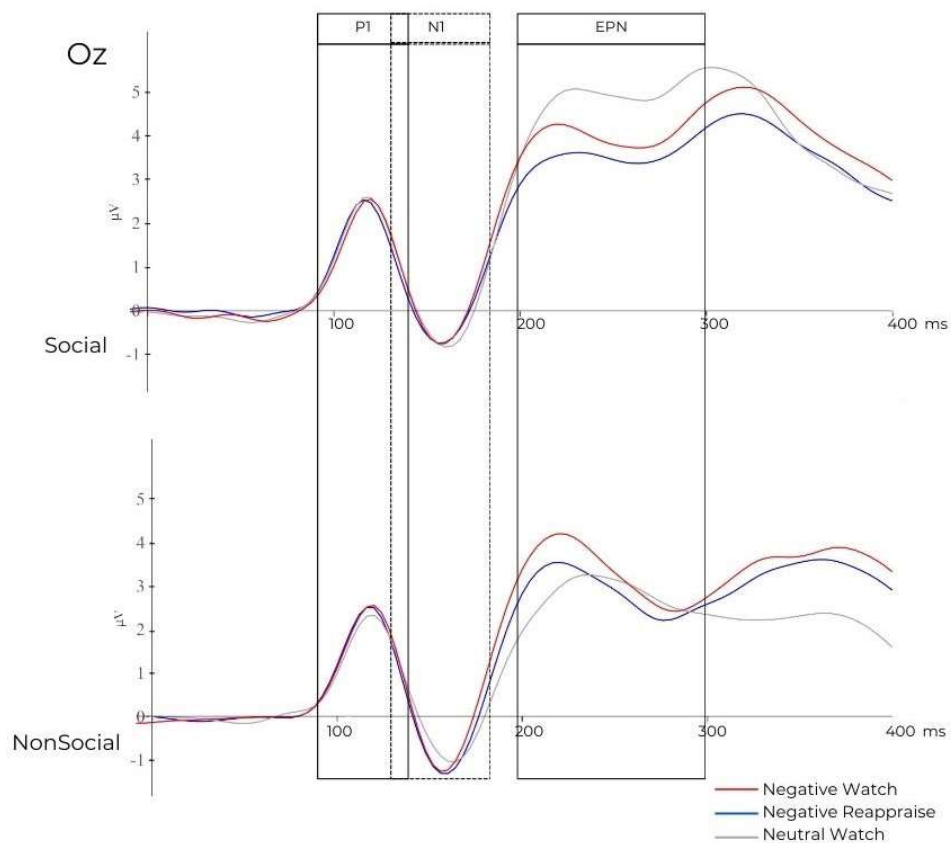
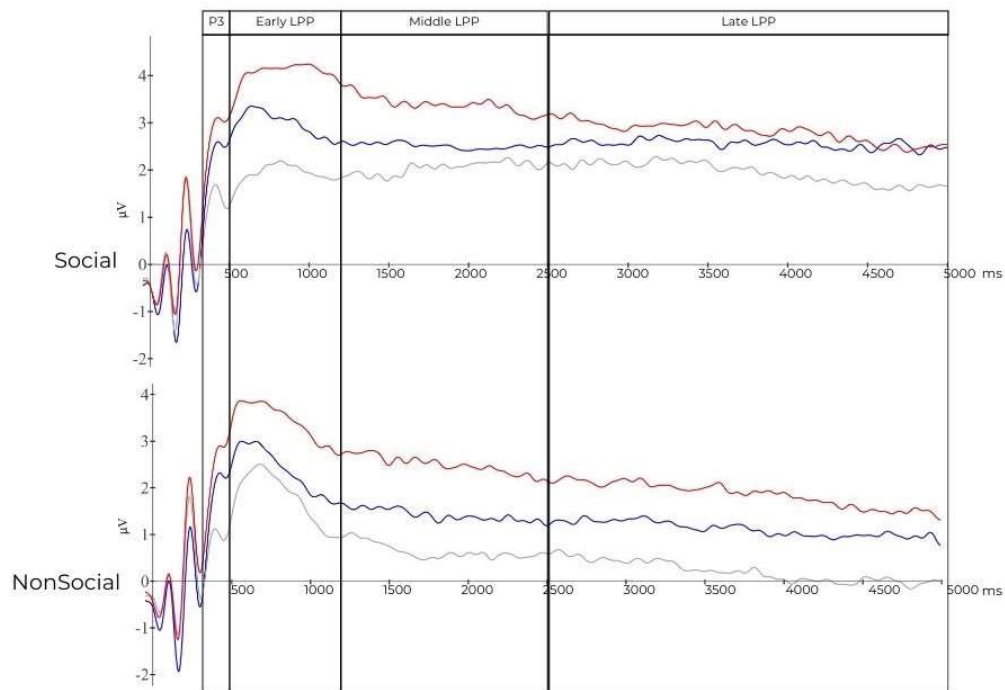


Figure 3. Average ERP waveforms. Top panel: Average ERP waveforms from the centroparietal region (CP1, CPz, CP2, P1, Pz, P2), segmented into four time windows: P3 (350–500 ms), Early LPP (500–1200 ms), Middle LPP (1200–2500 ms), and Late LPP (2500–5000 ms) time windows. Bottom panel: Average ERP waveforms at electrode Oz, highlighting the P1 (90–140 ms), N1 (130–190 ms),

and EPN (200–300 ms) components. Waveforms are displayed separately for social and nonsocial conditions, including Negative Watch, Negative Reappraise, and Neutral Watch. Abbreviation: ERP: Event-related potential; LPP: Late positive potential; EPN: Early posterior negativity

Effect of experimental conditions

Effect of experimental conditions on self-reported behavioral response

As expected, both social and nonsocial negative stimuli elicited significantly higher arousal and were rated as less pleasant than neutral stimuli (all $p < 0.001$, Cohen's $d = 1.7$ – 2.4 ; Figure 4). Furthermore, when negative social and nonsocial stimuli were reappraised rather than passively watched, participants rated them as significantly less arousing and more pleasant (all $p < 0.001$, Cohen's $d = 0.5$ – 1.3 ; Figure 4).

Effect of experimental conditions on GSR

Reappraised nonsocial negative stimuli elicited stronger GSR responses ($M = 0.011$, $SD = 0.016$) than passively watched social negative stimuli ($M = 0.009$, $SD = 0.015$; $t(130) = 3.31$, $p = 0.001$), suggesting heightened autonomic activation during reappraisal. For social negative stimuli, greater GSR responses were observed for negative stimuli ($M = 0.013$, $SD = 0.019$) than for neutral stimuli when passively watched ($M = 0.009$, $SD = 0.012$; $t(130) = 2.2$, $p = 0.028$). No other contrasts reached statistical significance.

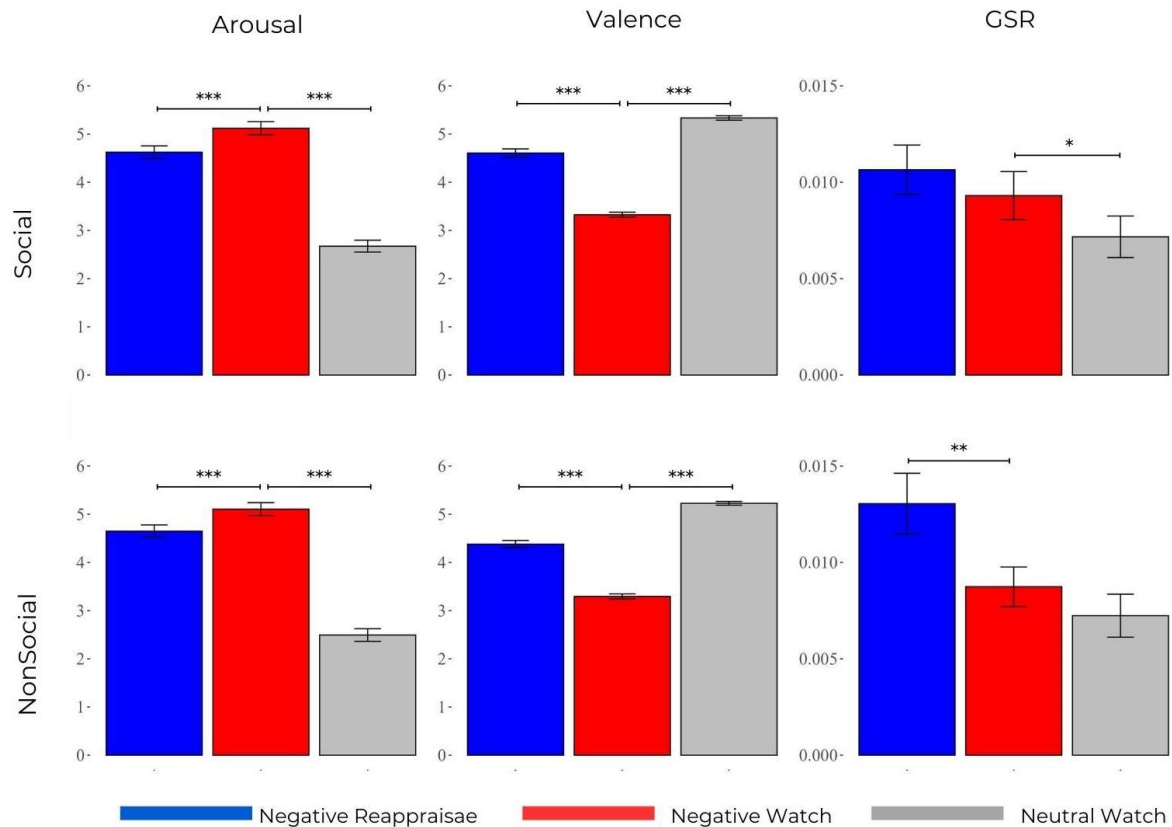


Figure 4. Mean levels of Arousal, Valence, and GSR across social and nonsocial conditions
Error bars represent the standard error of the mean.
Abbreviation: GSR, Galvanic Skin Response

Effect of experimental conditions on ERP

P1/N1: The P1 amplitude significantly differentiated between nonsocial negative and neutral stimuli ($t(146) = 2.99$, $p = 0.003$, Cohen's $d = 0.25$). In addition, N1 latency was shorter for nonsocial negative stimuli than for neutral stimuli ($t(146) = -4.5$, $p < 0.001$, Cohen's $d = 0.38$). However, no significant differences were observed between reappraised and passively watched stimuli.

EPN: For social stimuli, negative images elicited smaller amplitudes compared to neutral stimuli ($t(146) = -7.86$, Cohen's $d = -0.65$, $p < 0.001$). In contrast, for nonsocial stimuli, negative images evoked larger amplitudes ($t(146) = 4.71$, Cohen's $d = 0.39$, $p < 0.001$). Reappraised effects were observed in both stimuli types, with reappraised stimuli eliciting smaller amplitudes than passively watched negative stimuli for both social ($t(146) = -4.47$, Cohen's $d = -0.37$, $p < 0.001$) and nonsocial ($t(146) = -3.92$, Cohen's $d = -0.32$, $p < 0.001$).

P300/LPP: The P300 and all LPP components (early, middle, late) showed smaller amplitudes for passively watched neutral and reappraised negative stimuli than for passively watched negative stimuli (all $p < 0.009$, Cohen's $d = 0.22$ – 1.05). The only exception was the late LPP, where no significant difference was observed in the social negative vs. neutral contrast.

For a detailed breakdown of results, refer to Table S4 in the Supplementary Materials.

Association between loneliness and outcome measures

Association between loneliness and self-reported behavioral response to affective stimuli

More lonely participants reported decreased arousal to negative vs. neutral social stimuli, as indicated by self-reported ratings ($r(145) = -0.17$, $p = 0.037$). No such effect was found for arousal ratings of nonsocial stimuli ($r(145) = -0.11$, $p = .19$).

No association between participants' loneliness scores and valence ratings was observed (social: $r(145) = 0.11$, $p = 0.2$; nonsocial: $r(145) = 0.07$, $p = 0.39$).

Association between loneliness and neurophysiological response to affective stimuli

More lonely participants exhibited higher P300 differences for negative vs. neutral social stimuli ($r(145) = 0.19$, $p = 0.02$). However, no significant correlations were found for the remaining ERPs and GSR (r s between -0.12 and 0.10 , all $p > 0.25$).

Association between loneliness and self-report markers of cognitive reappraisal use

More lonely individuals reported less efficient cognitive reappraisal of arousal while watching social stimuli ($r(145) = 0.17, p = 0.04$) but not nonsocial stimuli ($r(145) = 0.09, p = 0.3$) stimuli. No association with valence was found across categories (social: $r(145) = -0.06, p = 0.5$; nonsocial: $r(145) = -0.06, p = 0.5$).

Association between loneliness and neurophysiological markers of cognitive reappraisal use

No significant associations were found for any of the analyzed neurophysiological markers of cognitive reappraisal use (r s between -0.12 and 0.10 , all $p > 0.15$)

For the full correlation matrix, see Table S5 in Supplementary Materials.

Mediation analysis

Relationship between loneliness and mediators

Loneliness was significantly associated with all considered mediators, except for Set-Shifting Cost ($r = -0.09, p = 0.28$). Importantly, loneliness showed a strong positive correlation with both social anxiety (LSAS: $r = 0.59, p < 0.001$) and depressive symptoms (CESD: $r = 0.54, p < 0.001$). In addition, loneliness was negatively correlated with cognitive reappraisal, as measured by the ERQ ($r = -0.332, p < 0.001$) and CERQ ($r = -0.406, p < 0.001$), suggesting that individuals who experience greater loneliness tend to employ less adaptive emotion regulation strategies. No other significant correlations between loneliness and mediators were found.

Relationship of dependent variables with mediators

Correlations between depression (CESD) and N1 amplitudes revealed that participants with higher levels of depressive symptoms exhibited a smaller early attentional bias toward social negative stimuli than toward neutral stimuli ($r(145) = -0.2, p = 0.017$). Set-shifting cost was negatively associated with difference scores for GSR and subjective arousal when comparing reappraised to passively watched negative stimuli (GSR: $r(129) = -0.18, p = 0.037$; arousal: $r(145) = -0.21, p = 0.01$). This suggests that greater difficulty in cognitive flexibility was linked to lower self-reported reappraisal efficiency and reduced GSR in the reappraisal condition compared to that in the negative condition. No other significant correlations between mediators and dependent variables were observed.

Mediation analyses

We conducted three mediation analyses to examine the indirect effects of psychophysiological measures on loneliness, using UCLA-R scores as the independent variable. Model 1 investigated the P300 difference wave (Watch Negative – Watch Neutral for social stimuli) as the dependent variable, with social anxiety (LSAS) and depressive symptoms (CESD) as mediators. Model 2 examined the arousal difference score (Watch Negative – Watch Neutral for social stimuli) as the dependent variable, with social anxiety (LSAS) and depressive symptoms (CESD) as mediators. Model 3 assessed the arousal difference score (Reappraise Negative – Watch Negative for social stimuli) as the dependent variable, with Set-Shifting Cost, the Cognitive Reappraisal subscale of the ERQ, and the Cognitive Reappraisal principal component of the CERQ as mediators.

Model 1: The total effect of loneliness on the P300 difference wave was significant ($B = 0.19, p = 0.016$), indicating that higher loneliness scores were associated with an increased P300 response to social negative vs. neutral stimuli. However, the direct effect of loneliness on the P300 difference wave was notably stronger ($B = 0.36, p < 0.001$), suggesting the presence of a suppression effect through social anxiety (LSAS). Specifically,

the indirect effect of loneliness via LSAS was significant but in the negative direction ($B = -0.129$, $p = 0.035$), partially counteracting the direct effect of loneliness. This pattern likely reflects a complex interplay where loneliness and social anxiety, despite being strongly positively correlated, exhibit opposing relationships with the P300 difference wave, leading to the observed suppression effect. In contrast, the indirect effect through depressive symptoms (CESD) was not significant ($B = -0.04$, $p = 0.47$). Path coefficients illustrating these relationships are presented in Figure 5a.

Model 2: A similar pattern is observed for the arousal difference score between observing negative social and neutral social stimuli. The total effect was significant ($B = -0.17$, $p = 0.035$), indicating that loneliness was linked to reduced differences in participants' self-reported arousal levels. The direct effect was stronger ($B = -0.23$, $p = 0.028$), while the indirect effect through social anxiety (LSAS) was also significant but in the opposite direction ($B = 0.14$, $p = 0.026$). The indirect effect through CESD was not significant ($B = -0.08$, $p = 0.158$). Path coefficients illustrating these effects are presented in Figure 5b.

Model 3: In the third model, no significant mediation effects were observed.

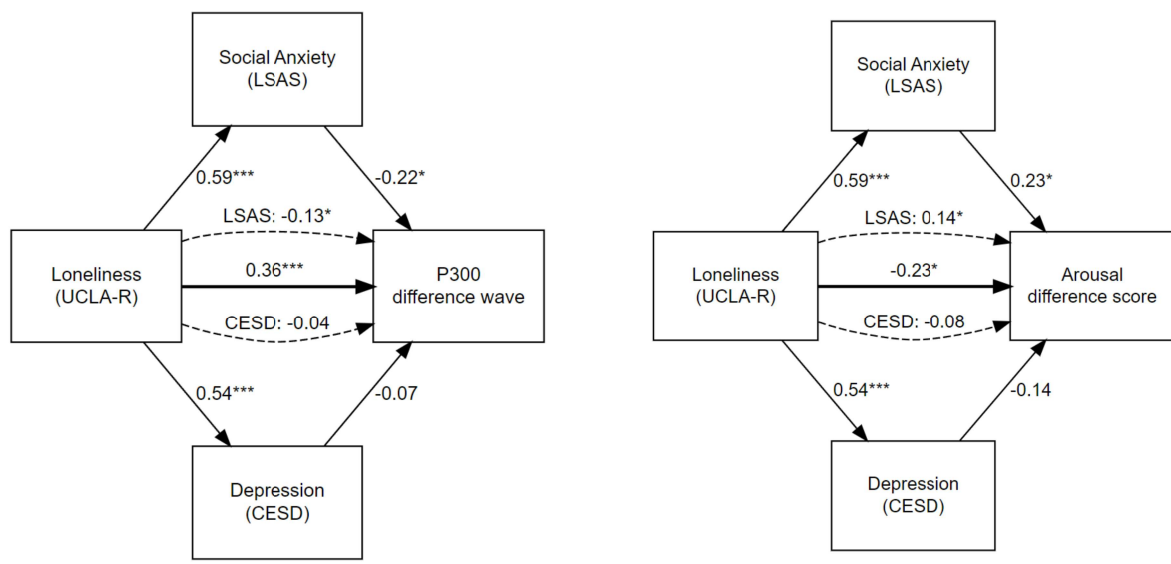


Figure 5. Mediation models. Solid arrows represent direct effects, while dashed arrows indicate indirect effects. Standardized regression coefficients are displayed alongside the arrows. Abbreviations: LSAS, Liebowitz Social Anxiety Scale; UCLA-R, University of California, Los Angeles Revised Loneliness Scale; CESD, Center for Epidemiologic Studies Depression Scale

Discussion

Loneliness has been identified as a strong predictor of negative health outcomes (Matthews et al., 2019), a relationship that has been attributed to abnormal responses to social negative stimuli (Spithoven et al., 2017). The present study aimed to examine the relationship between loneliness and behavioral and physiological markers of response to social and nonsocial stimuli. Furthermore, we investigated whether loneliness is linked to a reduced impact of cognitive reappraisal on self-reported and physiological responses to negative stimuli.

Consistent with extensive research on neurophysiological mechanisms underlying bottom-up affective response generation, we observed greater early, middle, and late ERP components, as well as increased GSR, arousal, and negativity ratings for negative than for neutral stimuli. Similarly, neurophysiological responses to negative (vs. neutral) stimuli were attenuated when participants employed cognitive reappraisal strategies, highlighting the effectiveness of top-down emotion regulation. The most pronounced bottom-up effects of stimulus content and top-down ERP modulation by reappraisal were observed within the first 2 s of posterior positivity. This aligns with previous findings that report stable and consistent LPP effects in ERP studies on affective stimulus encoding (Hajcak et al., 2010; Kennedy & Montreuil, 2020) and cognitive reappraisal (Harrison & Chassy, 2017; Thiruchselvam et al., 2011). Despite our predictions, we did not observe an association between loneliness and either early automatic (vigilance-related) ERPs or later-stage components considered markers of sustained response to motivationally salient stimuli. Notably, we found an association between loneliness and increased P300 amplitudes in response to negative social stimuli compared to that in response to neutral in our sample, which may reflect increased orienting of attention in lonely individuals (Hajcak & Foti, 2020). Secondly, given the extensive self-report literature suggesting an association between loneliness and increased negativity bias (Spithoven 2017), we expected to observe corresponding patterns

in self-reported ratings. However, a contradictory finding emerged: more lonely individuals reported a smaller subjective arousal difference between social negative and neutral stimuli, with no comparable effect for nonsocial stimuli.

This pattern suggested that loneliness is associated with an abnormal valuation of social stimuli. Previous studies have demonstrated that arousal ratings are primarily tracked by late positive ERP components (Rozenkrants et al., 2008). Based on this, we would expect decreased LPP amplitudes in more lonely individuals. However, contrary to our preregistered hypotheses, no differences in LPP were observed between groups.

Importantly, the present study examined whether the relationship between loneliness and stimulus-driven affective responses is further influenced by psychopathological factors that shape emotional reactivity. Although no mediating effects of depression were observed, social anxiety was found to suppress the effects of loneliness at both behavioral and neurophysiological levels. Our mediation analyses revealed that the loneliness-related reduction in subjective arousal towards negative social stimuli was less pronounced in participants with greater social anxiety, which aligns with existing literature indicating heightened negative evaluations of emotional stimuli in socially anxious people (Ziv et al., 2013). Further, controlling for social anxiety increased the correlation coefficient between P300 amplitude and loneliness when comparing social negative to neutral stimuli, from 0.19 to 0.36. This suggests that loneliness heightens attentional orienting toward negative social stimuli, whereas social anxiety counteracts this effect by dampening the physiological response. This pattern is consistent with previous studies showing reduced LPP amplitudes in response to negative social stimuli in socially anxious individuals (Weinberg & Hajcak, 2011); Mühlberger et al., 2009; Kausche et al., 2022).

In line with extensive literature showing LPP sensitivity to top-down emotion regulation strategies, a robust effect of cognitive reappraisal on LPP markers was observed across participants in the current sample. However, contrary to our hypothesis, no association between loneliness and LPP—or any other neurophysiological indicators of cognitive reappraisal use—was found in this well-powered sample, which is representative of

the loneliness distribution in the Polish population. On the other hand, self-report data indicated that greater loneliness levels were associated with a perceived decrease in subjective arousal reduction during cognitive reappraisal of negative social stimuli, which confirms previous self-reports suggesting weaker emotional regulation skills in lonely individuals (Patrichi et al., 2024). The dissociation between subjective and objective findings may indicate that loneliness is linked to lower self-efficacy in emotion regulation or reduced accuracy in assessing its effectiveness. Supporting the first interpretation, a recent study on coping self-efficacy suggests that loneliness is linked to a reduced sense of effectiveness in managing emotional challenges (Lee et al., 2023).

In conclusion, the findings of this study suggest that loneliness is linked to the volitional attentional orienting toward salient social stimuli. However, results indicate that lonely individuals exhibit typical affective responses, with no evidence of increased vigilance or sustained reactions to social threats. Instead, loneliness appears to be associated with altered behavioral threat appraisal processes, as reflected in subjective self-reported arousal ratings that do not align with objective neural data. This misalignment between subjective and objective measures of emotional responses may be attributed to two related constructs: alexithymia and interoceptive accuracy.

Alexithymia, characterized by difficulties in identifying and describing emotions, has been consistently linked to loneliness (Conti et al., 2023; Qualter et al., 2009). Interoceptive accuracy refers to the ability to perceive and interpret internal bodily signals associated with emotional states. A study using well-established Cyberball paradigm has shown that social exclusion can influence this ability, with socially excluded participants exhibiting decreased interoceptive accuracy (Durlak & Tsakiris, 2015). Arnold et al., 2019 suggest that this effect may result from a shift in attention from internally to externally focused during challenging social situations. Research on alexithymia and interoceptive accuracy suggests that loneliness is linked to altered self-evaluation of emotional responses, which may explain the discrepancy between subjective arousal ratings and objective neural data observed among lonely individuals in the present study.

The current study has some limitations worth noting. Firstly, we did not measure alexithymia or interoceptive accuracy, both of which could provide key insights into the observed behavioral results. Secondly, our study focused only on cognitive reappraisal as an emotion regulation strategy. However, since loneliness is linked to various emotion regulation strategies, differences may emerge in alternative strategies beyond cognitive reappraisal. Finally, while this study was preregistered and conducted within a confirmatory framework, EEG research inherently involves multiple statistical comparisons. Although our findings suggest an influence of loneliness on cognitive processing, it is important to acknowledge that many of the observed effects were close to the statistical significance threshold. If this study had been exploratory and applied corrections for multiple comparisons, most loneliness-related associations would not have reached significance. This highlights the challenges of detecting subtle effects in neurophysiological research. Rather than expecting strong predictive power from a single ERP measure, these findings should be interpreted with caution and require replication in large samples to confirm their robustness. Future studies could explore whether targeted neuromodulation interventions, such as transcranial direct current stimulation, might help mitigate the effects of reduced interoceptive accuracy in individuals experiencing loneliness.

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Supplementary Materials

Preregistration Deviations

Table S1

Preregistration deviations						
#	Details		Preregistration wording	Manuscript Wording	To what extent is this a deviation from the preregistered plan?	Reason
1	Type	Methods	EEG recording will then be also visually inspected to: 1/ remove large non-stationary artifacts and 2/ interpolate noise channels if necessary.	If more than 50% of trials in any Condition × Content cell were marked as artifacts, manual artifact rejection was performed to assess whether the data could be salvaged, with all annotations documented for full reproducibility.	Minor	Unification of EEG data preprocessing pipeline in all projects of the Social Neuroscience Lab.
	Reason	New knowledge				
	Timing	Before data access				
2	Type	Methods	Any residual artifacts which would result in an abnormally large signal (over +/-100 µV) will be rejected prior to the ERP extraction.	Trials with residual artifacts ($> \pm 100 \mu V$ in peak-to-peak amplitude within a 200 ms moving window and 100ms step) were rejected ($M = 9.3$, $SD = 16.2$, range = [0, 140]).	Minor	Unification of EEG data preprocessing pipeline in all projects of the Social Neuroscience Lab.
	Reason	New knowledge				
	Timing	Before data access				
3	Type	Methods	Each waveform and differential wave will be tested against a zero value. To adjust for multiple comparisons, Benjamini and Yekutieli algorithm for control of the false discovery rate will be used, as implemented in the mass univariate toolbox (Groppe et al., 2011).	T-tests were conducted at each electrode and time point (4–4996 ms), with false discovery rate correction (Benjamini & Hochberg, 1995) applied to control false positives at a nominal alpha level of 0.05.	Minor	Problems with Mass Univariate Toolbox
	Reason	New knowledge				
	Timing	After data access				
4	Type	Methods	Furthermore, data	-	Minor	Bad quality of ET

	Reason	Plan not possible	from the ET will be used to identify and reject unattended trials (when participants did not look at the screen on the picture longer than 50% of presentation time - 2.5s).			data.
	Timing	After data access				

Fig 1. Preregistration Deviation Table was adapted from Willroth and Atherton 2024.

Stimuli Selection

During the Emotion Processing and Regulation Task (EPRT), static pictures (negative and neutral pictures with social or nonsocial content) were presented to participants. Pictures for EPRT were selected from the Nencki Affective Picture System, International Affective Picture System, and Emo Madrid databases. In order to select pictures, an online pilot study was conducted. The original pictures pool consisted of 413 elements (133 non-social negative, 80 non-social neutral, 140 social negative, 60 social neutral) selected from databases. Half of the pictures were rated by 31 participants and the other half by 36 participants, all recruited online and aged between 18 and 35. Participants validating the pictures were matched by sex and age. Selection from IAPS and NAPS was based on their original validations (neutral: valence between 4 and 6, arousal < 5; negative: valence < 4, arousal: > 5). Additionally, the set of pictures was supplied by 12 neutral non-social and 18 neutral social pictures from the Emo Madrid database. Social pictures were selected to avoid presenting agents looking directly into the camera to avoid eliciting the effect of direct gaze. Participants were asked to rate the valence and arousal elicited by pictures on the 9-point self-assessment manikin scale (SAM). Subsequently, 80 neutral pictures (40 social and 40 nonsocial pictures with valence between 4 and 6 and arousal <5) and 160 negative pictures (80 social and 80 nonsocial pictures with valence < 4 and arousal >5) were selected.

Repeated measures ANOVAs to examine the effects of Content (2 levels: social, nonsocial) and Content (2 levels: negative, neutral) of the picture on arousal and valence ratings. Negative photos were rated as more arousing ($F(1, 236) = 1990, p < 0.001$) and more negative ($F(1, 236) = 2085, p < 0.001$), compared to Neutral pictures. Social and Nonsocial pictures did not differ in terms of mean arousal ($F(1, 236) = 0.79, p = 0.37$) or valence ($F(1, 236) = 0.73, p = 0.39$). Furthermore, no interaction between factors was observed. Next, photos were divided into six categories: Social Neutral Watch, Nonsocial Neutral Watch, Social Negative (Set A), Social Negative (Set B), Nonsocial Negative (Set C), Nonsocial Negative (Set D). Sets A and B and sets C and D were matched in terms of presented content, e.g. both set C and D presented a similar number of pictures of snakes, spiders, and guns.

One-way ANOVAs were used to examine whether the sets elicit a similar affective response in pilot-study participants. The four negative sets of stimuli did not differ in arousal ($F(3, 156) = 1.36, p = 0.26$) and valence ($F(3, 156) = 1, p = 0.39$). Social pictures were matched in terms of the number of people presented at them between affective categories (One way ANOVA with 2 level Emotionality factor: Neutral and Negative, $F(2, 117) = 1.29, p = 0.28$).

To rule out the possibility that non-content-related characteristics of the stimuli will drive any between-condition differences in early visual potentials, we have also compared the basic physical properties of pictures between sets. No between-set differences were found with regard to luminance ($F(5, 234) = 0.37, p = 0.87$) and contrast of the pictures ($F(5, 234) = 0.96, p = 0.44$). To avoid potential effects of sets, the presentation of the "Watch" and "Response" for each pair of sets (Set A vs Set B; Set C vs Set D) was counterbalanced between participants with regard to their gender and loneliness levels. A list of the final set of stimuli and their characteristics may be found here, <https://osf.io/uck7e>.

Experimental setup

Experimental task was programmed in PsychoPy version 2021.1.4. and was presented on the BENQ XL2546K monitor (24.5 inch) with 240 Hz refreshing rate. The edges of the stimuli were at 11.74 degree visual angle from the center of the screen. All stimuli were presented against a gray background (RGB 128, 128, 128).

Mediator Variables:

Revised UCLA Loneliness Scale

The UCLA-R (Kwiatkowska et al. 2017) is a 20-item questionnaire with statements about perceived social belonging and isolation. Each item is rated from 1 (Never) to 4 (Often). Higher scores are indicative of more pronounced loneliness. UCLA-R showed a high degree of reliability in the current sample (Cronbach's $\alpha = 0.94$).

The Set-shifting Task:

The Set-Shifting Task (McRae et al. 2012) assessed cognitive control by requiring participants to identify letters at different levels of visual hierarchy in switching and non-switching trials. Each stimulus consisted of letters at global level (large letters H or S) composed of letters at local level (small letters H or S). Based on a color cue, participants identified either the global (large) letter or the local (small) letters. Trials were either congruent (the same letter at both levels) or incongruent (different letters at global and local levels). In switching trials, the color cue changed, requiring participants to shift their focus between global and local levels, whereas in non-switching trials, the cue remained the same, allowing them to maintain their focus. A set-shifting metric was calculated as the difference in reaction times between switching and non-switching trials, reflecting cognitive flexibility. Set shifting cost was significantly different from 0 ($M = 93.8, SD = 73.3; t(146) = 15.53, p < 0.001$).

Center for Epidemiologic Studies Depression Scale-Revised (CESD-R)

Depressive symptoms were measured using the CESD-R (Kozlarska 2016), a 20-item self-rating scale that assesses depressive symptoms. Participants rate each item on a 0-3 Likert scale, where 0 represents "not at all" and 3 indicates "almost every day." The Polish version of the CESD-R has demonstrated good reliability and is appropriate for use in population-based samples. The total score is derived by summing the responses, with higher scores reflecting greater severity of depressive symptoms. CESD showed a high degree of reliability in the current sample (Cronbach's $\alpha = 0.93$).

Liebowitz Social Anxiety Scale (LSAS)

Social anxiety was assessed using the LSAS (Liebowitz 1987), a 24-item scale evaluating anxiety and avoidance in various social situations. The scale includes two subscales: one for anxiety/fear and another for avoidance. Participants rate (i) how anxious or fearful they would feel in each situation on a 0-3 scale (0 = none, 3 = severe) and (ii) how often they would avoid the situation on a 0-3 scale (0 = never, 3 = usually) during the week prior to the assessment. The total scores for both subscales are calculated by summing the corresponding responses, with higher scores reflecting more severe symptoms of social anxiety and avoidance. LSAS showed a high degree of reliability in the current sample (Cronbach's $\alpha = 0.95$).

Emotion Regulation Questionnaire (ERQ)

Emotion regulation strategy use was assessed with the ERQ (Gross and John 2012), a 10-item scale measuring participants' tendency to use cognitive reappraisal or expressive suppression as emotion regulation strategies. Items are rated on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree). Higher scores indicate a stronger tendency to use the respective emotion regulation strategy. LSAS showed an acceptable reliability in the current sample (Cronbach's $\alpha = 0.72$).

Cognitive Emotion Regulation Questionnaire (CERQ)

The CERQ (Marszał-Wiśniewska & Fajkowska, 2010) was used to assess the frequency of use of nine different emotion regulation strategies: self-blame, rumination, catastrophizing, other-blame, acceptance, positive refocusing, refocus on planning, putting into perspective, and positive reappraisal. The scale consists of 36 items, and participants are asked to rate how often they use each strategy on a 5-point scale (1 = never, 5 = always). Higher scores reflect more frequent use of each emotion regulation strategy. For the CERQ, dimension reduction was conducted using principal component analysis with promax rotation in the R *psych* package. The analysis identified a three-factor structure comprising Cognitive Reappraisal (26% of variance explained), Self-Blame (22% of variance explained), and Other-Blame (14% of variance explained). This structure was selected based on factors with eigenvalues above 1, which were used in subsequent analyses (see Supplementary Materials for further details). CERQ showed a high degree of reliability in the current sample (Cronbach's $\alpha = 0.81$). Loadings of CERQ Principal Components are provided in Table S2, Summary Statistics for Factors are provided in Table S3.

Supplementary Statistical analysis

If a significant effect was found in the difference waves or difference scores, additional analyses were conducted to correlate the raw measures (mean ERP waves, GSR, or rating scores) with loneliness, separately for each condition contributing to the respective difference wave/score. This investigated whether the observed effect could be attributed to the relationship between the participants' mean waves/score values in the conditions and loneliness.

Supplementary Results

Following the primary analyses, a secondary analysis was conducted to investigate whether the observed effects in the difference waves or behavioral scores were associated with the mean activity/rating of the conditions involved in the subtraction. Specifically, when significant correlations between the differential scores/waves and loneliness were found, further correlations with the mean ERP/score values for the relevant conditions were performed. However, this secondary analysis did not reveal any significant results.

Supplementary Tables

CERQ Subscale	RC1	RC2	RC3
Self-blame	-0.090	0.809	0.078
Acceptance	0.343	0.427	-0.128
Rumination	0.015	0.718	0.337
Positive refocusing	0.696	-0.420	0.335
Refocus on planning	0.573	0.346	-0.271
Positive reappraisal	0.870	-0.041	-0.067
Putting into perspective	0.693	0.013	0.095
Catastrophizing	-0.177	0.455	0.709
Other-blame	0.105	0.046	0.878

Table S2: Loadings of CERQ Principal Components

	RC1	RC2	RC3
SS loadings	2.220	1.859	1.609
Proportion Var	0.247	0.207	0.179
Cumulative Var	0.247	0.453	0.632

Table S3: Summary Statistics for Factors

Measure	Condition 1	Condition 2	Content	t	df	p	Cohen's d	Mean Condition 1	Mean Condition 2	Mean Difference	SD of Difference
Arousal	Negative Watch	Neutral Watch	Nonsocial	21.10	146	<0.001**	1.74	5.11	2.49	2.61	1.50
Arousal	Negative Watch	Neutral Watch	Social	21.93	146	<0.001**	1.81	5.12	2.67	2.45	1.35
Arousal	Negative Change	Negative Watch	Nonsocial	-6.40	146	<0.001**	-0.53	4.65	5.11	-0.46	0.87
Arousal	Negative Change	Negative Watch	Social	-7.28	146	<0.001**	-0.60	4.62	5.12	-0.50	0.83
Valence	Negative	Neutral	Nonsocial	-29.	14	<0.001*	-2.46	3.29	5.23	-1.93	0.78

	Watch	Watch	al	87	6	**					
Valence	Negative Watch	Neutral Watch	Social	-27.99	146	<0.001* **	-2.31	3.33	5.33	-2.01	0.87
Valence	Negative Change	Negative Watch	Nonsoci al	14.05	146	<0.001* **	1.16	4.38	3.29	1.09	0.94
Valence	Negative Change	Negative Watch	Social	15.20	146	<0.001* **	1.25	4.61	3.33	1.28	1.02
P300	Negative Watch	Neutral Watch	Nonsoci al	9.66	146	<0.001* **	0.80	2.70	1.04	1.66	2.09
P300	Negative Watch	Neutral Watch	Social	9.29	146	<0.001* **	0.77	2.98	1.44	1.54	2.01
P300	Negative Change	Negative Watch	Nonsoci al	-3.79	146	<0.001* **	-0.31	2.12	2.70	-0.58	1.87
P300	Negative Change	Negative Watch	Social	-3.62	146	<0.001* **	-0.30	2.43	2.98	-0.55	1.83
Early LPP	Negative Watch	Neutral Watch	Nonsoci al	8.68	146	<0.001* **	0.72	3.42	1.83	1.59	2.21
Early LPP	Negative Watch	Neutral Watch	Social	12.79	146	<0.001* **	1.05	4.13	1.98	2.14	2.03
Early LPP	Negative Change	Negative Watch	Nonsoci al	-5.94	146	<0.001* **	-0.49	2.40	3.42	-1.02	2.07
Early LPP	Negative Change	Negative Watch	Social	-6.66	146	<0.001* **	-0.55	3.04	4.13	-1.09	1.98
Middle LPP	Negative Watch	Neutral Watch	Nonsoci al	9.36	146	<0.001* **	0.77	2.49	0.68	1.81	2.35
Middle LPP	Negative Watch	Neutral Watch	Social	7.29	146	<0.001* **	0.60	3.45	2.08	1.37	2.29
Middle LPP	Negative Change	Negative Watch	Nonsoci al	-4.76	146	<0.001* **	-0.39	1.45	2.49	-1.04	2.65
Middle LPP	Negative Change	Negative Watch	Social	-4.28	146	<0.001* **	-0.35	2.54	3.45	-0.91	2.59
Late LPP	Negative Watch	Neutral Watch	Nonsoci al	7.52	146	<0.001* **	0.62	1.89	0.23	1.65	2.67
Late LPP	Negative Watch	Neutral Watch	Social	3.73	146	<0.001* **	0.31	2.89	1.96	0.93	3.01
Late LPP	Negative Change	Negative Watch	Nonsoci al	-2.69	146	0.008**	-0.22	1.18	1.89	-0.71	3.21
Late LPP	Negative Change	Negative Watch	Social	-1.17	146	0.242	-0.10	2.60	2.89	-0.29	3.01
N1 latency	Negative Watch	Neutral Watch	Nonsoci al	-4.55	146	<0.001* **	-0.38	157.63	162.15	-4.52	12.04
N1 latency	Negative Watch	Neutral Watch	Social	-1.20	146	0.231	-0.10	158.64	159.76	-1.12	11.25
N1 latency	Negative Change	Negative Watch	Nonsoci al	1.24	146	0.217	0.10	158.80	157.63	1.17	11.44
N1 latency	Negative Change	Negative Watch	Social	-1.24	146	0.218	-0.10	157.22	158.64	-1.41	13.86
N1 peak	Negative	Neutral	Nonsoci al	-1.7	14	0.091	-0.14	-1.92	-1.70	-0.22	1.54

	Watch	Watch	al	0	6						
N1 peak	Negative Watch	Neutral Watch	Social	1.66	14 6	0.100	0.14	-1.40	-1.57	0.18	1.29
N1 peak	Negative Change	Negative Watch	Nonsoci al	-0.1 0	14 6	0.924	-0.01	-1.93	-1.92	-0.01	1.47
N1 peak	Negative Change	Negative Watch	Social	-0.6 6	14 6	0.509	-0.05	-1.48	-1.40	-0.08	1.49
P1 latency	Negative Watch	Neutral Watch	Nonsoci al	0.26	14 6	0.794	0.02	117.47	117.14	0.33	15.13
P1 latency	Negative Watch	Neutral Watch	Social	-0.4 4	14 6	0.658	-0.04	117.58	118.10	-0.52	14.13
P1 latency	Negative Change	Negative Watch	Nonsoci al	1.38	14 6	0.169	0.11	118.94	117.47	1.47	12.90
P1 latency	Negative Change	Negative Watch	Social	-0.2 2	14 6	0.825	-0.02	117.33	117.58	-0.24	13.43
P1 peak	Negative Watch	Neutral Watch	Nonsoci al	2.99	14 6	0.003**	0.25	3.50	3.15	0.34	1.39
P1 peak	Negative Watch	Neutral Watch	Social	0.77	14 6	0.441	0.06	3.39	3.29	0.10	1.54
P1 peak	Negative Change	Negative Watch	Nonsoci al	-1.9 6	14 6	0.052	-0.16	3.28	3.50	-0.22	1.36
P1 peak	Negative Change	Negative Watch	Social	-0.3 8	14 6	0.705	-0.03	3.33	3.39	-0.05	1.71
EPN	Negative Watch	Neutral Watch	Nonsoci al	4.71	14 6	<0.001* **	0.39	3.27	2.77	0.50	1.30
EPN	Negative Watch	Neutral Watch	Social	-7.8 6	14 6	<0.001* **	-0.65	4.03	4.88	-0.85	1.32
EPN	Negative Change	Negative Watch	Nonsoci al	-3.9 2	14 6	<0.001* **	-0.32	2.85	3.27	-0.42	1.30
EPN	Negative Change	Negative Watch	Social	-4.4 7	14 6	<0.001* **	-0.37	3.53	4.03	-0.50	1.35
GSR	Negative Watch	Neutral Watch	Nonsoci al	1.46	13 0	0.147	0.13	0.01	0.01	0.00	0.01
GSR	Negative Watch	Neutral Watch	Social	2.22	13 0	0.028*	0.19	0.01	0.01	0.00	0.01
GSR	Negative Change	Negative Watch	Nonsoci al	3.31	13 0	0.001**	0.29	0.01	0.01	0.00	0.01
GSR	Negative Change	Negative Watch	Social	1.50	13 0	0.136	0.13	0.01	0.01	0.00	0.01

Table S4. Results of t-tests and descriptive statistics for analyzed contrasts in the study.

Measure	Social	Nonsocial	Social	Nonsocial
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	Reappraise vs Negative	Reappraise vs Negative	Negative vs Neutral	Negative vs Neutral
Arousal	0.169*	0.085	-0.172*	-0.109
Valence	-0.056	-0.056	0.105	0.071
GSR	-0.091	-0.032	0.007	0.010
P1 peak	-0.076	-0.151	0.054	0.021
P1 latency	0.049	-0.033	-0.007	-0.007
N1 peak	-0.025	-0.042	-0.072	-0.024
N1 latency	0.071	-0.091	-0.094	0.017
EPN	-0.060	0.026	0.045	-0.086
P300	-0.074	-0.069	0.194*	0.122
Early LPP	0.012	-0.054	0.090	0.042
Middle LPP	0.068	-0.027	-0.006	-0.038
Late LPP	0.047	0.011	-0.072	-0.104

Table S5. Correlation table of measures with UCLA-R loneliness scale for four contrasts.

Supplementary Figures:

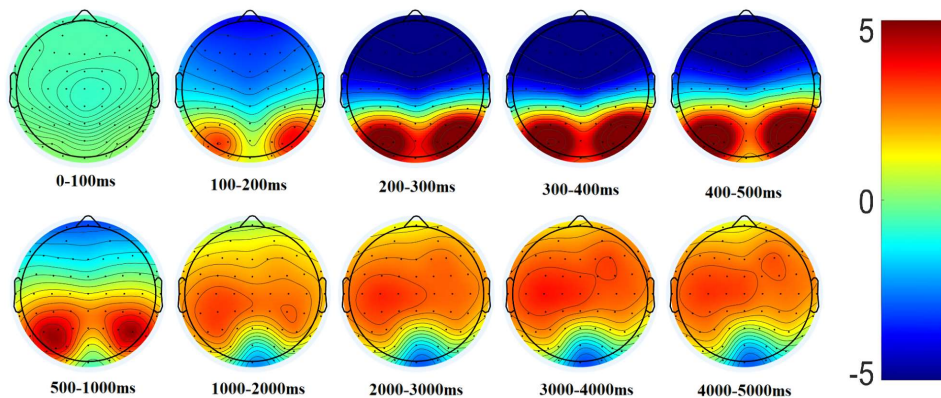


Figure S1. The grand-average scalp topography of the event-related potentials.

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Investigating trajectories linking social cognitive capacity, bias, and social isolation using computational modeling

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Abstract

Despite theoretical emphasis on loneliness affecting social information processing, empirical studies lack consensus. We previously adopted a clinical science framework to measure the association between social cognitive capacity and bias and both objective and perceived social isolation in nonclinical participants. Our prior study found that while objective social isolation is linked to both social cognitive capacity and social cognitive bias, loneliness is associated only with the latter. This study extended our previous model using a computational approach to capture implicit cognitive processes. We replicated and extended our earlier findings with a new sample of 271 participants, using neuropsychological tasks and a dot-probe paradigm that was analyzed via Drift Diffusion Model. We presented two complementary trajectories of how social cognitive bias may arise: the increased propensity to engage with salient social stimuli or a decreased information processing capacity dependent on the presence or absence of potential social threats. Furthermore, we found evidence that loneliness is associated with the time needed for perceptual processing of stimuli, both directly and indirectly, via social cognitive bias. Taken together, the complex and context-dependent nature of information processing biases observed in the current study suggests that complex and multifaceted interventions should be implemented to counter social information processing biases in lonely individuals.

Keywords: loneliness; social cognition; cognitive bias; drift diffusion modeling; social isolation

Introduction

Loneliness [i.e. perceived social isolation (PSI)] is a subjective state of discrepancy between the quantity or quality of one's desired and actual social relationships (Perlman and Peplau 1981). Empirical studies have established that loneliness and objective social isolation are distinct psychosocial constructs that exhibit a weak to moderate relationship with each other (Taylor 2020, Okruszek et al. 2021). Some studies indicate that loneliness has the most detrimental effect on mental well-being (Cho et al. 2019, Park et al. 2023), while other researchers emphasize that both phenomena are partially independent risk factors for overall adverse health outcomes (Holt-Lunstad et al. 2015, Ma et al. 2021, Cené et al. 2022, Kelsall-Foreman et al. 2023). Given the fact that loneliness is driven by one's subjective perception of one's social relationships, rather than by objective characteristics of one's social functioning, a lot of attention has been focused on factors that may drive social appraisals in chronically lonely individuals who, according to the currently predominant conceptualization [Evolutionary Theory of Loneliness (ETL); Cacioppo and Cacioppo 2018], may display increased orienting to social cues which may be biased toward social threat hypervigilance. At the same time,

empirical support for such mechanisms is rather limited, with studies examining the association between loneliness and social cognitive processes associated with social perception or emotion processing yielding contradictory results (Spithoven et al. 2017). However, as evidenced by previous research in this field, divergent conclusions of the previous studies may be partially accounted for by the methodological factors; for example, the use of *ad hoc* measures with no known psychometric properties and varying conceptualizations of social cognitive processes. Thus, in the largest in sample size up-to-date behavioral study investigating social cognitive mechanisms in loneliness, we have adapted a comprehensive and well-validated battery of neuropsychological tasks (Pinkham et al. 2018) to measure in a psychometrically valid manner the association between social cognitive capacity (SCC) and objective and perceived social isolation in a large cohort of nonclinical participants (Okruszek et al. 2021). This way, we were able to show that while Objective Social Isolation (OSI) is linked both to low-level processing of social cues [as grasped by social perception and emotion recognition Social Cognition Psychometric Evaluation (SCOPE) tasks] and social cognitive bias (SCB), loneliness is associated only with the latter (Okruszek et al. 2021).

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While there is general agreement that lonely individuals may show a negative SCB, i.e. systematic tendency to appraise social stimuli in a negative manner, rather than objective reductions or deficits across social cognitive domains, the lack of a clear approach to how to operationalize and measure such a bias may constitute a clear challenge for future studies investigating social information processing in lonely individuals. Importantly, despite the calls to extend the measurement of constructs underlying normal and abnormal behavior by combining multilevel information from genetic, molecular, physiological, behavioral, and self-report data (e.g. RDoC; [Morris and Cuthbert 2012](#)), research on SCB rarely goes beyond a single level of explanation to combine multiple units of analysis ([Pinkham et al. 2016](#), [Kaurin et al. 2022](#)). Furthermore, the way such a bias is conceptualized is often driven by the field of investigation, e.g. while schizophrenia research focuses on a tendency to interpret ambiguous or neutral social cues as indicative of hostile or aggressive intent from others ([Combs et al. 2007](#), [van der Gaag et al. 2013](#)), studies on anxiety disorders tend to investigate perceptual or attentional processes associated with the involuntary tendency toward preferential processing of threatening or negative social stimuli ([Cisler and Koster 2010](#), [Pergamin-Hight et al. 2015](#)).

While large-scale inclusion of physiological behavioral markers into loneliness research may not be attainable, one potential way to address the limited reliability of behavioral markers obtained via typical overt measures (i.e. self-report, behavioral accuracies, and reaction times) is to derive implicit behavioral parameters from explicit behavioral data via computational modeling. By formalizing the behavioral outcomes using mathematical models, one may uncover implicit parameters directly linked to specific cognitive systems and avoid caveats associated with analyzing overt outcomes, which may be a juxtaposition of multiple covert factors ([Wilson and Collins 2019](#)). One such approach, the Drift Diffusion Model (DDM; [Ratcliff and McKoon 2008](#)), has proved to be a particularly promising tool for investigating perceptual and social decision-making processes. The DDM can break down behavioral outcomes from forced-choice action tasks into parameters associated directly with accumulating evidence in favor of one of various options and extraneous sensory or motor processes contributing to an overt behavioral response. This property of the DDM approach has been successfully utilized by [Price et al. \(2019\)](#), who showed that DDM nondecision time has better psychometric properties for studying the impact of social threat on sensory processes in individuals with social anxiety compared to standard behavioral parameters extracted from a dot-probe task. Interestingly, we recently presented preliminary evidence that, compared to nonlonely counterparts, lonely individuals may show a decreased information accumulation rate, as indicated by the DDM drift, rather than an increased susceptibility to the impact of negative social stimuli, as indicated by nondecision time in the dot-probe task ([Mąka et al. 2023](#)).

Thus, the aim of the current study is to establish a multilevel model of social information processing in loneliness by replicating our previous findings in a novel cohort of individuals and extending our model by linking overt measures included in it to covert DDM parameters. This way, we can examine whether the previously established link between loneliness and SCB stems from a reduced information processing capacity ([Mąka et al. 2023](#)) or an increased susceptibility to the impact of negative social stimuli on socio-perceptual decision-making processes ([Price et al. 2019](#)) in lonely individuals.

Methods

Participants

Data for the current study were pooled from two projects investigating the neurophysiological underpinnings of loneliness (National Centre of Science, Poland 2018/31/B/HS6/02848 and 2019/35/B/HS6/00517, PI: Ł.O.). Sample 1 consisted of 163 individuals who were recruited to correspond with the distribution of the Revised UCLA Loneliness Scale (UCLA-R) scores in a Polish population. Sample 2 included 108 individuals with UCLA-R scores corresponding to the lowest (Q1) or highest (Q4) scores in a Polish population. In total, 271 right-handed individuals (150 females) aged 18–35 years ($M = 24.94$, $SD = 4.54$ y.o.) with no history of substance abuse, cardiovascular or neurological disorders, and, in the case of Sample 2, Magnetic Resonance Imaging contraindications were recruited via social media platforms. Participants were also screened for current depressive episodes as indicated by anhedonia and dysphoria cut-off scores in the Polish version of the revised Center for Epidemiologic Studies Depression Scale ([Kozłara 2016](#)).

The study procedure was held at the Institute of Psychology PAS in Warsaw. Each participant provided informed written consent to the project-specific procedures, which were the same for each of the projects. The behavioral and self-report procedures described below were approved by the Ethical Committee at the Institute of Psychology, PAS (decisions 21/XI/2019 and 16/VI/2021). A post-hoc power analysis, conducted using the “pwr” R package, indicated that a sample size of 271 participants would provide sufficient statistical power (80%) to detect a Pearson correlation coefficient of 0.17.

Assessment of social cognitive capacity and bias

In alignment with distinctions in clinical neuroscience, we define SCC as the ability to perform information processing functions, typically assessed through performance-based measures related to social perception, emotion recognition, and theory of mind. In contrast, SCB refers to information processing functions that lead to systematically distorted outputs, measured using vignette-based (Ambiguous Intentions Hostility Questionnaire, AIHQ; [Combs et al. 2007](#)) and self-assessment questionnaires (Davos Assessment of the Cognitive Biases Scale, DACOBS; [van der Gaag et al., 2013](#)) that assess attribution and hostility biases ([Roberts and Pinkham 2012](#)). The assessment of SCC in our study was based on tasks recommended by the SCOPE consortium ([Pinkham et al. 2018](#)). These tasks, which were either available or previously validated in Polish by our team, have been effectively utilized in studies on social cognitive mechanisms in both clinical ([Okuszek et al. 2022](#)) and nonclinical ([Okuszek et al. 2021](#)) populations. The battery included four tasks—The Mini Profile of Nonverbal Sensitivity (MiniPONS), the Penn Emotion Recognition Task (PENN ER-40), the Reading the Mind in the Eyes Task (RMET), and the Hinting Task (HT)—covering social perception, emotion processing, and mentalizing processes. Our selection of these social cognition measures was guided not only by their psychometric properties but also by the relative simplicity of adapting these tasks to Polish. Notably, the PENN ER-40 and HT have been highly recommended by [Pinkham et al. \(2018\)](#) for their robust psychometric properties. However, it is important to acknowledge recent critiques of some of these measures. The MiniPONS has faced criticism regarding its psychometric properties, prompting Pinkham and colleagues to recommend caution in

Table 1. Summary statistics for measures of SCC and SCB ($N=270$, one participant was excluded due to an insufficient number of responses in the dot-probe task)

	PENN ER40	PONSS	HINTING	RMET	AIHQ BS	DACOBS 42 AB
Mean	82%	47.2	17	26.1	2.7	22.9
SD	8%	4	2.2	3.3	0.6	6.1
Minimum	50%	36	8	14	1	0
Maximum	97%	58	20	34	4	38
Ceiling scores	0	0	21	0	–	–

AIHQ BS, Ambiguous Intentions Hostility Questionnaire Blame Score; DACOBS42 AB, Davos Assessment of Cognitive Biases Scale Attribution Bias subscale; PENN ER-40, Penn Emotion Recognition Task ER-40.

its use. Similarly, the psychometric properties of the RMET have been questioned, concerning both its validity and reliability (Higgins et al. 2023). Despite these concerns, in our present sample, all performance-based measures showed correlations with other measures of social cognition, suggesting their continued relevance in capturing various aspects of social cognitive processes. A detailed description of each task may be found in supplementary materials. Descriptive statistics for measures of social capacity and social bias are provided in Table 1. We investigated ceiling effects in SCOPE tasks—they were found only in the case of HTs, with 21 out of 271 (7.7%) participants scoring the maximum possible score on it.

Assessment of social functioning

In line with our previous research in this area (Okruszek et al. 2021, 2023), the Polish version of the UCLA-R (Kwiatkowska et al. 2017) was used to measure loneliness in participants. The UCLA-R is a 20-item questionnaire with statements about perceived social belonging and isolation. Each item is rated from 1 (Never) to 4 (Often). Higher scores are indicative of more pronounced loneliness. A six-item version of the Lubben Social Network Scale (SNS; Lubben 1988) was used to measure OSI in participants. Two sets of three questions are given to measure the number of relatives and friends, respectively, with whom the participant: (i) is in regular contact, (ii) may seek help from, and (iii) may confide in. The main outcome is the sum of the six questions. For the parsimony, the SNS scores have been reversed, so higher scores may reflect a more pronounced OSI. Both of the measures showed a high degree of reliability in the current sample (Cronbach's $\alpha = 0.94$ for UCLA-R, $\alpha = 0.84$ for SNS).

Dot-probe task

Each trial of the task started with the presentation of a white fixation cross for 500 ms, followed by the appearance of two pictures of the same actor placed on either side of the fixation cross (CUE) for 200 ms. After that, a target stimulus (a colon placed either horizontally or vertically, either on the right or on the left side of the fixation cross) was presented for 1000 ms. Participants were instructed to respond by pressing either a right or left arrow key depending on the orientation (vertical or horizontal, respectively) of the colon. The presentation side and orientation of the colon were counterbalanced between trials. The task was presented in two runs of 160 trials each. During the first run, only neutral faces were presented, while in the second run, each trial presented one angry and one neutral face. The face of the same actor was presented twice, once for each block. The facial stimuli consisted of 160 faces of 80 actors, obtained from the FACES database (Ebner et al. 2010) and cropped for the purpose of the current study. The presentation of the neutral/angry stimuli was counterbalanced with regard to the sex of the actors, target positions, and

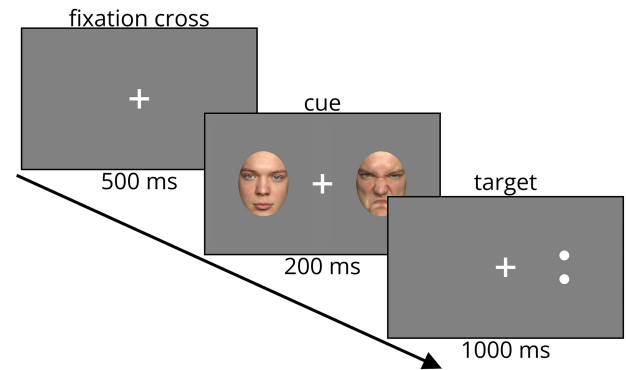


Figure 1. A schema of a trial from the dot-probe task.

correct response to target. Before starting the main task, participants underwent training, which included 12 trials without cue and 24 full trials. The experimental procedure was programmed using Neurobehavioral Systems Presentation software (version 21.1). The structure of the task is presented in Fig. 1.

DDM parameters estimation

The preprocessing of behavioral data and estimation of DDM parameters were carried out using R 4.1.1 (R Core Team, 2013). Trials with no behavioral response, responses faster than 200 ms, and reaction times exceeding two standard deviations from the mean for each participant within each condition were excluded from the analysis. One participant was excluded due to an insufficient (<50%) number of responses in the task. The model was set with five free parameters: drift rate (v), nondecision time (t_0), threshold separation (a), variability of t_0 (st_0), and variability in v (sv). The starting point parameter z was set as a threshold divided by two ($a/2$), due to model specification with boundaries representing correct and incorrect responses, respectively. The differential evolution Markov Chain Monte Carlo was used as an estimation procedure based on Hawkins et al. (2017). The convergence of the chains was checked using the Multivariate Potential Scale Factor (MPSF; Brooks and Gelman 1998). The MPSF for all participants was below 1.15, indicating that the chains converged successfully. We calculated t_0 and v separately for neutral-neutral (baseline) and neutral-angry conditions. To assess psychometric properties of these measures, an odd-even reliability analysis was conducted using intraclass correlation coefficient—ICC(2,1)—version in Shrout and Fleiss (1979) nomenclature. The code used to estimate DDM parameters may be found at (<https://osf.io/7xvfg/>). Next, we evaluated whether there was a difference in DDM parameters between dot-probe conditions. A paired samples t -test was conducted to compare the scores between the baseline and angry conditions for both nondecision time (t_0) and drift rate (v). For nondecision time (t_0), there was a significant difference in the scores between the baseline ($M = 0.347$, $SD = 0.039$) and angry condition ($M = 0.343$, $SD = 0.039$); $t(269) = 2.50$, $P = .013$. For drift rate (v), there was also a significant difference between the baseline ($M = 4.098$, $SD = 0.443$) and angry condition ($M = 4.003$, $SD = 0.483$); $t(269) = 4.80$, $P < .001$. Thus, the presence of threatening stimuli decreases the accumulation rate of task-related information, as evidenced by a lower drift rate, while simultaneously reducing reaction time due to nondecisional processes.

Statistical analysis

In line with the original study (Okruszek et al. 2021), in the first step of the analysis, zero-order correlations were calculated between main social cognition, social functioning, and dot-probe

DDM measures. Next, we examined whether the original model incorporating overt measures indicating SCC, SCB, and social isolation was replicated in the sample by combining 271 participants from the current study. For a detailed description of the model, please see Okruszek et al. (2021). Then, we fitted the model by combining 271 participants from the current study with 252 participants from the original (Okruszek et al. 2021) study. This analysis is provided in supplementary materials. Finally, to examine the associations between DDM parameters and overt measures, we examined a new Structural Equation Modeling (SEM) model which includes three types of variable: (i) two outcomes (OSI and PSI), which were entered as two correlated observed variables; (ii) two latent variables corresponding to SCOPE variables [SCC (MiniPONS, PENN ER-40, RMET, Hinting) and SCB (DACOBS42 AB, AIHQ BS)] which were entered as correlated predictors of OSI and PSI; and (iii) two DDM parameters (t_0 and v) which, due to their joint modeling, were entered as correlated observed variables and entered as predictors of (i) and (ii) variables. In the SEM approach, exogenous variables—such as drift rate and non-decision time in this context—are typically modeled as correlated by default. This is because, in the absence of predictors, their covariance cannot be explained by other variables in the model. Consequently, their interrelationship remains unexplained. For endogenous variables, while their relationships with exogenous variables are specified, the covariance between these endogenous variables may not be fully accounted for by these relationships alone, suggesting the presence of unexplained covariance due to other potential factors. Since the pair of variables OSI and PSI, as well as SCC and SCB, show stronger correlations with each other compared to their correlations with their respective predictors in the model, we decided to account for their residual covariance by modeling them as correlated within the model.

SEM models were fitted separately for the DDM parameters (t_0 and v) extracted from the baseline (Model 1) and neutral–angry (Model 2) trials. We have chosen this approach to account for potential differences in the underlying cognitive processes between the two conditions. By modeling the baseline and neutral–angry trials separately, we aimed to capture condition-specific relationships between the parameters, which may be influenced by the introduction of threatening stimuli. SEM analysis was performed using the Lavaan package (0.6-16), and model fit was assessed using a comparative fit index ($CFI > 0.95$) and the root mean square error of approximation ($RMSEA < 0.06$) indices. Statistical inference of model fit was conducted with chi-squared statistics.

Results

Correlational analysis

Zero-order correlations from the current sample may be seen in Table 2.

Model with overt data

In a sample of 270 participants (150 F/120 M, 24.9 ± 4.5 y.o.), the original three-factor solution (Okruszek et al. 2021: Lower-Level Social Cue Perception, Higher Level Mentalizing, SCB) was poorly fitted ($\chi^2(15) = 47.10$, $P < .001$; $RMSEA = 0.08$; $CFI = 0.900$). However, the two-factor solution encapsulating all four original SCOPE measures under one latent variable (SCC) provided a good fit to the data ($\chi^2(16) = 22.51$, $P = .127$; $RMSEA = 0.03$; $CFI = 0.98$) and was further utilized. The variables included in the model

Table 2. Zero-order correlations from the current sample.

Variable	Nondecision time baseline	Nondecision time angry	Drift rate baseline	Drift rate angry	AIHQ BS	DACOBS42 AB	PENN ER-40	MiniPONS	RMET	HT	PSI
Nondecision time angry	0.738***										
Drift rate baseline	0.213**	0.129*									
Drift rate angry	0.195***	0.220***	0.758***								
AIHQ BS	0.077	0.150*	−0.044	−0.013							
DACOBS42 AB	0.003	0.108	−0.145*	−0.030	0.383***						
PENN ER-40	0.016	0.039	0.233**	0.197*	−0.086	−0.148*					
MiniPONS	0.080	0.086	0.162**	0.146*	−0.009	−0.212**	0.282**				
RMET	−0.051	−0.045	0.151*	0.123*	−0.025	−0.084	0.297**	0.266***			
HT	0.021	0.108	0.085	0.066	−0.013	−0.192*	0.161*	0.226**	0.249**		
PSI	−0.122*	−0.063	−0.125*	−0.095	0.367***	0.371***	−0.138*	−0.194**	−0.110	−0.065	
OSI	−0.017	0.057	−0.124*	−0.100	0.198*	0.283***	−0.161*	−0.238**	−0.204***	−0.100	0.591***

AIHQ BS, Ambiguous Intentions Hostility Questionnaire Blame Score; DACOBS42 AB, Davos Assessment of Cognitive Biases Scale Attribution Bias 42 item subscale; PENN ER-40, Penn Emotion Recognition Task ER-40; PSI, Perceived Social Isolation; OSI, Objective Social Isolation.

* $P \leq .05$,

** $P \leq .01$,

*** $P \leq .001$.

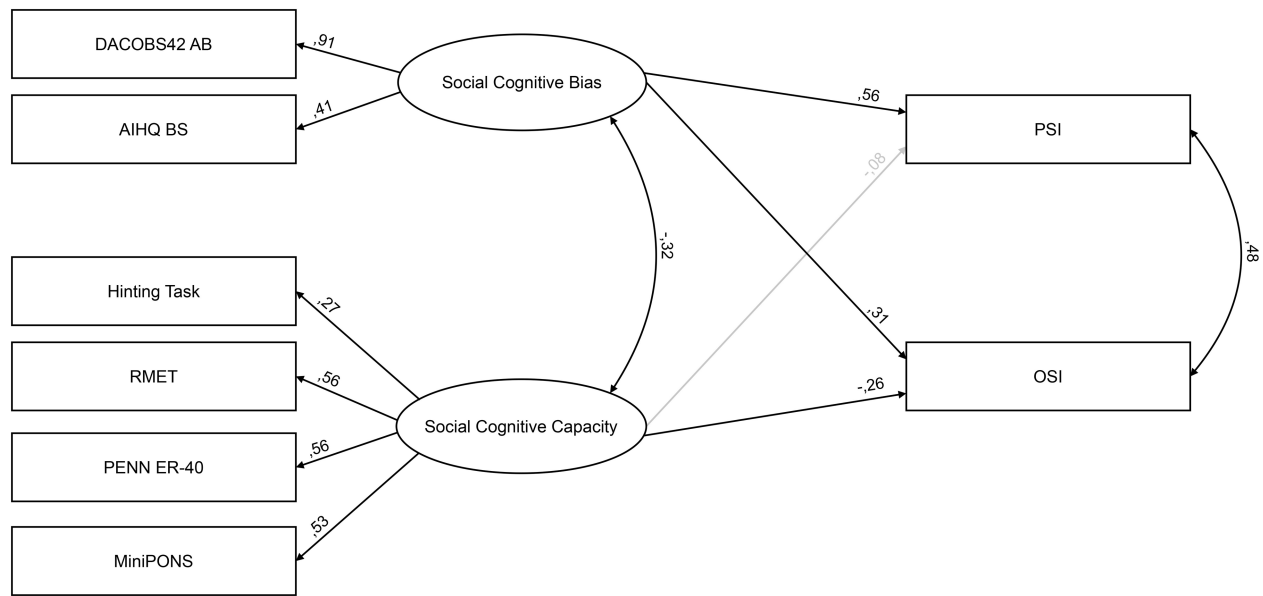


Figure 2. The SEM model with overt data, rectangles depict observable variables, while ellipses symbolize latent factors.

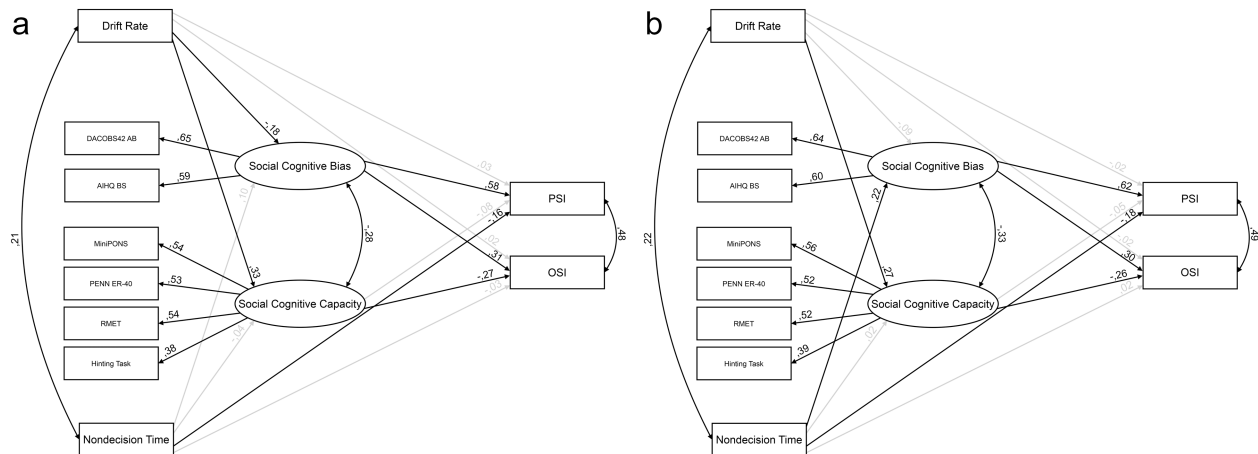


Figure 3. The SEM models of baseline (a; Model 1) and neutral-angry condition (b; Model 2).

explained over one third of the variance in the PSI (35%) and 22% of the OSI variance.

In line with our previous observations, positive correlations were observed between OSI and PSI ($r = 0.48$, $P < .001$) and negative between SCC and SCB ($r = -0.32$, $P < .001$). Similarly, in line with our previous report, SCB was linked to both PSI ($\beta = 0.56$, $P < .001$) and OSI ($\beta = 0.31$, $P < .001$), while SCC was a predictor of OSI ($\beta = -0.26$, $P < .001$), but not of PSI ($\beta = -0.08$, $P = .4$). Model is presented on Fig. 2.

Extended model with DDM parameters

Model 1, which is shown in Fig. 3a, had a good fit to the data [$\chi^2(24) = 30.35$, $P = .174$; RMSEA = 0.031; CFI = 0.982]. Model 2, depicted in Fig. 3b, also exhibited a favorable fit to the data, as evidenced by statistical indices [$\chi^2(24) = 32.45$, $P = .116$, RMSEA = 0.036, CFI = 0.976]. In each case, a considerable portion of the variability in PSI (Model 1–38%; Model 2–40%) and OSI (22% in both models) was accounted for by the model predictors.

Notably, intercorrelations were found between OSI and PSI (Model 1 $r = 0.48$, $P < .001$; Model 2 $r = 0.49$, $P < .001$), v and t_0 (Model 1 $r = 0.21$, $P = .001$; Model 2 $r = 0.22$, $P < .001$), and SCC and SCB (Model 1 $r = -0.28$, $P = .017$; Model 2 $r = -0.33$, $P = .006$).

DDM parameters were significantly linked to overt social cognitive outcomes: in both models v was found to be linked to SCC (Model 1 $\beta = 0.33$, $P < .001$; Model 2 $\beta = 0.27$, $P = .002$). Furthermore, v in the baseline trials (Model 1) was also weakly associated with SCB ($\beta = -0.18$, $P = .032$). In neutral-angry trials (Model 2), t_0 was found to predict SCB ($\beta = 0.22$, $P = .008$).

In line with our analysis of overt data from the pooled set of 523 participants, SCB emerged as a robust predictor of both PSI (Model 1: $\beta = 0.58$, Model 2: $\beta = 0.62$, $P < .001$) and OSI (Model 1: $\beta = 0.31$, $P = .001$; Model 2: $\beta = 0.30$, $P = .002$), while SCC was negatively associated only with OSI (Model 1: $\beta = -0.27$, $P = .006$; Model 2 $\beta = -0.26$, $P = .007$).

No direct association between v and outcome variables was observed. At the same time, t_0 showed a weak negative association with PSI (Model 1: $\beta = -0.16$, $P = .007$; Model 2: $\beta = -0.18$, $P = .005$).

Given the associations between DDM parameters and SCC/SCB, we also investigated indirect effects and found that v is indirectly negatively linked to OSI through SCC (Model 1 $\beta = -0.09$, $P = .016$; Model 2 $\beta = -0.07$, $P = .029$), and, in the case of Model 2, t_0 is indirectly positively linked to OSI through SCC ($\beta = 0.70$, $P = .038$). Finally, a positive relationship between t_0 and PSI was found through SCB for negative-angry trials ($\beta = 0.14$, $P = .014$), thus implying the presence of a suppressing effect in Model 2.

Discussion

The purpose of the current study was to extend the model of trajectories linking social cognitive mechanisms with social isolation initially presented by Okruszek et al. (2021). We used computational modeling to analyze a well-established social information processing task. This allowed us to introduce parameters that signify implicit processes associated with social information processing.

In the first step of the analysis, we corroborated our initial findings by showing that loneliness is linked to SCB, but not to SCC, both in the novel replication sample of 271 nonclinical individuals and in the pooled sample of 523 individuals. Given the clear two-factor structure of social cognitive measures observed in the current data, the findings provide robust evidence that while objective social isolation is linked to objective SCC, no such link can be found for subjective feelings of loneliness. At the same time, SCB, as measured by specific tendencies to appraise others' actions and intentions in a self-threatening manner, may be linked to both objective social isolation and subjective perception of one's relationships as lacking.

Secondly, we investigated the trajectories linking overt social cognitive outcomes with implicit processes indicated by DDM parameters. In line with previous findings highlighting the role of the DDM drift rate (v) as a reliable marker of perceptual learning processes (Liu and Watanabe 2012), working memory and reasoning (Schmiedek et al. 2007), and cognitive control (Spanler et al. 2022), we found a positive association between drift rate (v) and SCC in participants. A more complex trajectory was, however, observed for the association between DDM parameters and SCB: in line with previous reports suggesting that nondecision time (t_0) may be linked to bias measures in clinical anxiety (Price et al. 2019), we found a positive relationship between nondecision time (t_0) in threat-related trials and SCB in participants. However, when no threat was present (neutral-neutral block of trials), participants' SCB was predicted by their information processing capacity, as indicated by drift rate (v), not by nondecision processes, including attentional engagement with social stimuli, as indicated by nondecision time (t_0).

By its very definition, cognitive bias may be defined as a "systematic error in judgment and decision-making (...) which can be due to cognitive limitations, motivational factors, and/or adaptations to natural environments" (Mata 2012, p. 531). Thus, we hypothesize that, while in the presence of threat-related stimuli, high levels of SCB may reflect the tendency to be more captured by salient stimuli; under no-threat circumstances it may simply reflect participants' tendency to use simplified heuristics in social situations due to their reduced social information processing capacity.

Finally, by introducing DDM parameters into the model, we were able to link objective and perceived social isolation with latent cognitive processes signified by such parameters. First, we found an indirect relationship linking information

processing capacity, as indicated by drift rate (v), with objective social isolation via SCC, which may indicate a bilateral association between information capacity and actual opportunities for social interaction. Furthermore, a two-fold relationship between loneliness and DDM parameters was found. First, loneliness was negatively linked to nondecision time (t_0), which suggests that participants with higher levels of chronic loneliness may exhibit facilitated processing of social stimuli independently of its salience. However, in the absence of a nonsocial control task, it cannot be concluded whether this effect represents an increased orienting specifically toward social stimuli, which could be congruent with evolutionary accounts of loneliness (Cacioppo and Cacioppo 2018) or generalized alternations of perceptual decision-making mechanisms in lonely individuals. Secondly, the opposite indirect effect, with PSI being positively linked to nondecision time (t_0) via SCB, was also found in the presence of threat-related stimuli. This finding suggests that two opposite-direction effects may link PSI with nondecision time (t_0) in the presence of negative social stimuli, which may account for previous contradictory findings regarding the association between loneliness and attentional bias to threats (Spithoven et al. 2017).

Taken together, the current findings provide a robust and replicable model linking social isolation variables with social cognitive mechanisms in nonclinical participants. Using a computational modeling approach in loneliness research, we were able to differentiate between implicit processes associated with information processing efficiency and nondecision processes associated with vigilance toward salient stimuli. This way, we were able to provide two complementary accounts of how SCB may arise either due to the increased propensity to engage with salient social stimuli or to decreased information processing capacity dependent on the presence or absence of potential social threats. Finally, we provided evidence that loneliness is associated with nondecision time, both directly and indirectly, via SCB. Importantly, we demonstrated that in the presence of social threats, these two associations have opposite effects, resulting in suppression. Explicit behavioral or self-report measures can be thus insufficient to fully grasp the cognitive mechanisms of loneliness.

Still, several limitations of the current study should be noted: first, due to the construction of our sample and inclusion of a subgroup of participants with either very low or very high loneliness scores, the distribution of the loneliness may not be fully representative of the general sample. Secondly, methodological concerns have been raised with regard to the use of the dot-probe paradigm to study attentional processes (Kappenman et al. 2014); thus, the current results should be replicated across different paradigms. Finally, given the wealth of literature on neural bases of attentional bias, the current investigation could be extended to examine the extent to which DDM parameters are linked with actual neural processes underlying cognitive computations (Price et al. 2019, Mąka et al. 2023).

Supplementary data

Supplementary data is available at SCAN online.

Conflict of interest: None declared.

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Data availability

Data and code used in this study are available on the OSF repository at <https://osf.io/7xvfg/>.

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